Multi-scale Transactive Control In Interconnected Bulk Power Systems Under High Renewable Energy Supply and High Demand Response Scenarios

by

David P. Chassin BSc., Building Science, Rensselaer Polytechnic Institute, 1987 MASc., Mechanical Engineering, University of Victoria, 2015

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ABSTRACT

This dissertation presents the design, analysis, and validation of a hierarchical transactive control system that engages demand response resources to enhance the integration of renewable electricity generation resources. This control system joins energy, capacity and regulation markets together in a unified homeostatic and economically efficient electricity operation that increases total surplus while improving reliability and decreasing carbon emissions from fossil-based generation resources.

The work encompasses: (1) the derivation of a short-term demand response model suitable for transactive control systems and its validation with field demonstration data; (2) an aggregate load model that enables effective control of large populations of thermal loads using a new type of thermostat (discrete time with zero deadband); (3) a methodology for optimally controlling response to frequency deviations while tracking schedule area exports in areas that have high penetration of both intermittent renewable resources and fast-acting demand response; and (4) the development of a system-wide (continental interconnection) scale strategy for optimal power trajectory and resource dispatch based on a shift from primarily energy cost-based approach to a primarily ramping cost-based one.

The results show that multi-layer transactive control systems can be constructed, will enhance renewable resource utilization, and will operate in a coordinated manner with bulk power systems that include both regions with and without organized power markets. Estimates of Western Electric Coordinating Council (WECC) system cost savings under target renewable energy generation levels resulting from the proposed system exceed US\$150B annually by the year 2024, when compared to the existing control system.

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Nomenclature

- \overline{P} Expectated price average; in \$/MWh (demand response).
- \overline{Q} Mean heating system power; in W (aggregation).
- \bar{q} The population average device load; in MW (aggregation).
- \bar{R} The population average duty cycle; unitless (aggregation).
- \bar{r}_{off} The unweighted mean rate of temperature change of all devices that are off; °C/s (aggregation).
- \bar{r}_{on} The unweighted mean rate of temperature change of all devices that are *on*; °C/s (aggregation).
- $\bar{\rho}$ Mean thermostat duty cycle; unitless (demand response).
- β Price response function parameter; unitless (demand response).
- $\ddot{\tau}$ The second time derivative of the indoor air temperature; °C/s² (aggregation).
- \ddot{Q} Ramping rate of change; in MW/h² (dispatch).
- $\Delta \tau$ The actual temperature deviation from the desired temperature τ_D ; in °C (aggregation).
- $\Delta f(t)$ System frequency deviation; in Hz (regulation).
- $\Delta Q(t)$ Area net power exports deviation; in MW (regulation).
- $\Delta Q_s(t)$ Disturbance magnitude; in MW (regulation).
- Δt The elapsed time in a state; in seconds (aggregation).
- δ The hysteresis band half-width; in °F (aggregation).

- $\dot{\tau}$ The rate at which a device temperature changes; in °C/s (aggregation).
- \dot{Q} Ramping; in MW/h (dispatch).
- \dot{Q}^* Discrete power at next time step; in MW (dispatch).
- \dot{Q}_0 Initial ramping; in MW/h (dispatch).
- \dot{Q}_T Terminal ramping; in MW/h (dispatch).
- η_D Demand elasticity; unitless (demand response).
- $\hat{a}_s(s)$ Filtered ACE signal in *s*-domain (regulation).
- $\hat{f}(s)$ Interconnection frequency response in *s*-domain (regulation).
- $\hat{f}(s)$ System frequency; in s-domain (regulation).
- $\hat{g}_d(s)$ Droop-controlled generation response; in s-domain (regulation).
- $\hat{g}_r(s)$ ACE-controlled generation response response in s-domain (regulation).
- $\hat{l}(s)$ Load response in *s*-domain (regulation).
- $\hat{Q}(s)$ Interconnection power response in s-domain (regulation).
- λ Lagrange multiplier (including Q_z); in \$/MWh (dispatch).
- **c** The output gains $\begin{bmatrix} c_1 & c_2 \end{bmatrix}$; 2 × 1 vector (aggregation).
- **c** The output vector $\begin{bmatrix} \bar{q} & 0 \end{bmatrix}$; 2 × 1 vector (aggregation).
- **h** The input gains $\begin{bmatrix} h_1 \\ h_2 \end{bmatrix}$; 2 × 1 vector (aggregation).
- \mathbf{K}_c The observer output control gain model vector; 2×1 vector (aggregation).

x The system state
$$\begin{bmatrix} x_1 \\ x_2 \end{bmatrix}$$
; 2 × 1 vector (aggregation).

- $\tilde{\mathbf{c}}$ The observer output model vector; 2×1 vector (aggregation).
- $\tilde{\mathbf{h}}$ The observer input model vector; 2×1 vector (aggregation).
- μ Lagrange multiplier (excluding Q_z); in \$/MWh (dispatch).
- ν Linear demand response scale function; unitless (demand response).

- ω Square root of energy to ramping marginal price ratio; in h⁻¹ (dispatch).
- ρ Duty cycle of thermostatic load; unitless (demand response).
- ρ'_{off} The complimentary load-weighted population average rate of temperature change for devices that are off; °C/s (aggregation).
- ρ'_{on} The complimentary load-weighted population average rate of temperature change for devices that are on; °C/s (aggregation).
- ρ_{off} The load-weighted population average rate of temperature change for devices that are off; in °C/s (aggregation).
- ρ_{on} The load-weighted population average rate of temperature change for devices that are on; in °C/s (aggregation).
- $\sigma(Q)$ Load entropy; unitless (demand response).
- σ^2 The variance of the rate of change of indoor air temperature; °C/s (aggregation).
- σ_0 Maximum load entropy; unitless (demand response).
- σ_{off}^2 The variance of the rate of change of indoor air temperature when the heating/cooling system is off; °C/s (aggregation).
- σ_{on}^2 The variance of the rate of change of indoor air temperature when the heating/cooling system is on; °C/s (aggregation).
- τ The device temperature; in °C (aggregation).
- τ_A The temperature of the indoor air; °C (aggregation).
- τ_D The desired device temperature; in °C (aggregation).
- τ_M The temperature of the solid mass; °C (aggregation).
- τ_O The outdoor air temperature; °C (aggregation).
- τ_{hys} Thermstatic control hysteresis; in °F (demand response).
- τ_{obs} Observed thermostat state; in °F (demand response).

- τ_{off} Duration of 'off' period for thermostatic load; in hours (demand response).
- τ_{off} The temperature of a device that is off; °C (aggregation).
- τ_{off} Thermostatic steady state when 'off'; in °F (demand response).
- τ_{on} Duration of 'on' period for thermostatic load; in hours (demand response).
- τ_{on} The temperature of a device that is on; °C (aggregation).
- τ_{on} Thermostatic steady state when 'on'; in °F (demand response).
- τ_{set} Thermostat set point ; in °F(demand response).
- \tilde{P} Expectated price standard deviation; in \$/MWh (demand response).
- A cost parameter; unit varies according to context (dispatch).
- *a* Load price response function zero-order constant; unitless (demand response).
- a Marginal price of energy; in $MW^2 \cdot h$ (dispatch).
- a The principal pole of the discrete-time system model; in s^{-1} (aggregation).
- A(t) Raw ACE signal; in MW (regulation).
- *B* A cost parameter; unit varies according to context (dispatch).
- B Bid price; in MWh (demand response).
- *B* Frequency control bias; in MW/Hz (regulation).
- *b* Load price response function first-order constant; unitless (demand response).
- b Marginal price of power; in MW^2 (dispatch).
- b The principal zero of the discrete-time system model; in s^{-1} (aggregation).
- C A cost parameter; unit varies according to context (dispatch).
- C The system controllability matrix; 2×2 matrix (aggregation).
- c Marginal price of ramping; in $-MW^2$ (dispatch).
- C(t) Cost over the time interval 0 to t; in \$ (dispatch).

C^*	Cost associated with discrete time control; in \$ (dispatch).
c_1	The average load of a unit of n_{on} devices; in MW (aggregation).
c_2	The average load of a unit of n_{off} devices; in MW (aggregation).
C_A	The heat capacity of the indoor air; in J/K (aggregation).
C_M	The heat capacity of the solid mass; in J/K (aggregation).
C_{base}	Cost associated with base case control; in \$ (dispatch).
COP	HVAC system efficiency; unitless (aggregation).
D	A cost parameter; unit varies according to context (dispatch).
D	Interconnection damping constant; per unit (regulation).
d	Disturbance magnitude; in MW (regulation).
$d(kt_d)$	Slope of the load demand curve at the dispatch point; in MW^2h (regulation).
D_q	Load diversity at order q ; unitless (demand response).
E(t)	Energy over the time interval 0 to t ; in MWh (dispatch).
E_{Δ}	Energy demand parameter; in MWh (dispatch).
E_T	Energy over T ; in MWh (dispatch).
eta(P)) Demand elasticity at the price P ; unitless (demand response).
F(s)	Low-pass ACE control signal filter transfer function (regulation).
f(t)	System frequency; in Hz.

- F_d Fraction of total load that can be responsive to frequency (regulation).
- F_r Fraction of generating units that are ACE-controlled (regulation).
- f_s Nominal or scheduled system frequency; in Hz.
- G The state transition matrix of the population of devices; 2 × 2 matrix (aggregation).

- g(k) Load probability function; unitless (demand response).
- $G(t, Q, \dot{Q})$ Cost Lagrangian; in \$ (dispatch).
- $G_d(s)$ Droop-controlled generation response transfer function (regulation).
- $G_r(s)$ ACE-controlled generation resource transfer function (regulation).
- G_{pd} The proportional-derivative control transfer function; unitless (aggregation).
- *H* Shannon entropy of load; unitless (demand response).
- h The observer scalar reference input gain; unitless (aggregation).
- H(s) Interconnection overall transfer function (regulation).
- h_1 The net number of devices added to the controlled on population of devices by a unity input signal; unitless (aggregation).
- h_2 The net number of devices added to the controlled off population of devices by a unity input signal; unitless (aggregation).
- K Bid comfort control setting; in MWh.°F (demand response).
- K The closed-loop proportional control gain; unitless (aggregation).
- k Discrete time step; in p.u. t_s (dispatch).
- k The discrete time index such that $t = kt_s$; unitless (aggregation).
- k Thermostatic device population count; unitless (demand response).
- k_1 The derivative gain of the closed-loop proportional-derivative control; in seconds (aggregation).
- k_2 The proportional gain of the closed-loop proportional-derivative control; unitless (aggregation).
- K_d Fraction of total load that is armed by 5-minute dispatch (regulation).
- K_l Load control recovery time constant; in seconds (regulation).
- K_p Load quasi-steady rebound response time constant; in seconds (regulation).

- K_q The observer integral error feedback control gain model scalar; unitess (aggregation).
- L(s) Load transfer function (regulation).
- *M* Interconnection inertial constant; in seconds (regulation).
- N Number of thermostats under control; unitless (demand response).
- N_C Number of controllers; unitless (aggregation).
- n_{off} Number of devices that are off but not locked; unitless (aggregation).
- n_{off}^* Number of devices that are locked off; unitless (aggregation).
- n_{on} Number of devices that are on but not locked; unitless (aggregation).
- n_{on}^* Number of devices that are locked on; unitless (aggregation).
- O The system observability matrix; 2×2 matrix (aggregation).
- P(Q) Power price function; in \$/MWh (dispatch).
- P(t) Regulation energy price; in \$/MWh (regulation).
- P_d 5-minute dispatch energy price; in \$/MWh.
- P_s Hourly schedule energy price; in \$/MWh.
- Q Heating system power demand; in W (aggregation).
- Q Load; in MW (demand response).
- q The augmented state for integral error feedback control; in J (aggregation).
- q The total heat added to the device; in W (aggregation).
- Q(t) Actual net exports from a control area; in MW (regulation).
- Q(t) Total power; in MW (dispatch).
- Q^* Discrete power; in MW (dispatch).
- Q_0 Initial load; in MW (dispatch).

- Q_{Δ} Power demand parameter; in MW (dispatch).
- Q_E Scheduled load; in MW (dispatch).
- q_H Heating system output; in W (aggregation).
- q_I The heat added from internal, solar and ventilation gains; in W (aggregation).
- Q_R Most probable load; in MW (demand response).
- Q_s Scheduled net exports from a control area; in MW (regulation).
- q_S The heat added/removed by the heating/cooling system; in W (aggregation).
- Q_T Terminal load; in MW (dispatch).
- Q_U Unresponsive load; in MW (demand response).
- Q_z Must-take generation; in MW (dispatch).
- R Droop control constant; unitless (regulation).
- r Thermstatic state decay rate ; in °F/h (demand response).
- $R(Q, \dot{Q})$ Ramping price function; in \$/MW (dispatch).
- r_{off} The rate at which a device temperature changes when off; in °C/s (aggregation).
- r_{on} The rate at which a device temperature changes when on; in °C/s (aggregation).
- s Frequency domain complex variable; in h^{-1} (dispatch).
- s The Laplace domain complex variable s; in s⁻¹ (aggregation).
- $s(kt_d)$ Slope of the generation supply curve at the dispatch point; in MW^2h (regulation).
- T Interval terminating time; in hours (dispatch).
- t Real time variable; in seconds.
- *t* Time domain real variable; in hours (dispatch).

- T_f ACE control signal filter time constant in seconds (regulation).
- T_q Generation resource governor time constant; in seconds (regulation).
- T_l Load control derivative response gain (regulation).
- t_r Discrete control discrete-time sampling rate; in seconds (scheduling).
- t_s Discrete control discrete-time sampling rate; in hours (scheduling).
- t_s The discrete controller sampling time; in seconds (aggregation).
- t_s Time step; in seconds (dispatch).
- T_{ch} Generation resource steam chest time constant; in seconds (regulation).
- t_{min} The minimum control lockout time; in seconds (aggregation).
- U The z-domain transformation of the input u (aggregation).
- U_A The thermal conductivity between indoor and outdoor air; in W/K (aggregation).
- U_M The thermal conductivity between indoor air and solid mass; in W/K (aggregation).
- W(z) Lambert W-function; unitless (demand response).
- x_1 The first state of the state vector **x**, which is the number of devices on, n_{on} ; unitless (aggregation).
- x_2 The first state of the state vector **x**, which is the number of devices off, n_{off} ; unitless (aggregation).
- Y The z-domain transformation of the output y (aggregation).
- y The net load of the population of controlled devices.
- z The discrete-time z-domain variable $z = e^{-st}$; unitless (aggregation).
- z_1, z_2 The desired poles for the integral error feedback control design; in s⁻¹ (aggregation).

 z_q The desired dominant pole for the integral error feedback ground; in s⁻¹ (aggregation).

ACKNOWLEDGEMENTS

Most honest stories about how one gets something done probably should start with a confession, and mine is a long one. I consider it above average hubris when I say I hope to accomplish something that others might find useful enough for me to be remembered well after I am gone. I think this is what normal people of a certain age do. But mine is actually no greater a sin than looking for a change of scenery when in 1992 after 10 years in upstate New York I quit graduate school and left my successful start-up company after I became disillusioned with both architecture as a field of research and the stressful life of an entrepreneur.

I went west to the desert of central Washington State to start over with no expectations and no grand vision. I certainly did not know anything about, least of all expect to be more than an "extra" in the momentous changes that were coming to the electric power industry. In any event, I certainly had no inkling how my decision to start over could lead me through Victoria to Menlo Park writing these words. Now I only hope to set the record as straight as I recall it.

When I arrived at Pacific Northwest National Laboratory I began a twenty year series of more or less random encounters and collaborations with people who together would change the way I saw and understood the world of large-scale engineered systems and set me thinking about how and why one would go about trying to change the way we design and operate them.

In the mid-1990s, sensing diminished research returns in the already-crowded field of building energy efficiency I began looking for something new and exciting on which to work. At the Laboratory Richard Quadrel was beginning ground-breaking research on architecture and engineering design tools that employed the latest artificial intelligence methods. Michael Brambley was just starting a new program in building system diagnostics. Together they turned me to the world of engineering design tools and the question of how one uses automation to improve system operation through advanced controls and diagnostics. Robert Pratt was just coming off the seminal end-use load characterization and assessment program for Bonneville Power Administration, which provided a wealth of data about building energy consumption at the end-use level. Although budget cuts were a constant threat, I was very fortunate to lead the Building Sciences group just at a time when we began thinking about what would be the next big thing in buildings research.

At that time I shared an office suite with Landis Kannberg who managed the

electric power engineering group. Jeff Dagle and Matt Donnelly were among the people who began asking similar questions from the electric grid perspective and it was inevitable that these two groups would join forces. By 1999 the nugget of an idea borne of long hours thinking and talking about what might happen if buildings were more actively part of the power system operations.

This notion became the Energy Systems Transformation Initiative. Initially, Steve Hauser was hired to manage the initiative. He brought a grand vision and a wealth of connections to people who shared it. (Among them was Jesse Berst who Steve credits with coining the term "transactive", although I didn't learn that until years later). Soon after his arrival Steve drew on my whiteboard a simple taxonomy for how end-use devices are controlled in energy systems. This taxonomy has become one the key elements of what we (and some now regret) call the "smart grid".

- **Passive:** Devices that simply react to their environment and cannot take action autonomously to adjust in any non-trivial way. A conventional household thermostat is passive because if the price of electricity goes up or the frequency of the grid drops suddenly, it keeps on going without regard to anything other than what the temperature of your home is.
- Active: Devices that engage in more intelligent responses such as reducing consumption when prices rise or frequency drops, but do so in a completely autonomous manner without input from the user of the device.
- **Interactive:** Devices that act on the basis of interactions with consumers. Such a device might not reduce consumption as much when prices are high if you are having a dinner party or your elderly parent is staying with you during a heat wave.
- **Transactive:** Devices that exchange information with other devices to help the system as a whole find a more efficient way to operate.

Steve made one vital contribution to my understanding of this taxonomy: it doesn't apply a value judgment on devices in the different categories, i.e., active isn't better than passive or worse than interactive. But it does tell us something about what we should expect from devices in each class. The next 10 years of research became about understanding those expectations and how one would go about designing and operating an entirely new kind of system using them. Soon after the initiative began, Ross Guttromson joined the Laboratory. He brought a pragmatic approach to engineering from his years in the nuclear navy and working for large industrial engineering firms. One of his first assignments was to work with me to develop a new kind of simulation environment that would allow us to study what this new system might do. The product of that collaboration became the US Department of Energy's premiere tool for simulating the smart grid. Now known as GridLAB-D, I managed its development until 2013 and so it naturally ends up figuring prominently in the present work. Eric Lightner at the US Department of Energy's Office of Electricity realized early on the need for such a tool and provided the funding needed to ensure it was delivered and supported for the many years it needed to mature and become accepted by the smart grid research community.

Meanwhile, Donald Hammerstrom was chosen in 2005 to lead a project to demonstrate some of the Laboratory's initial thinking in this area. Together with Lynne Kiesling and Preston Michie, we planned, designed, deployed, operated and analyzed what is widely regarded now as the first operational retail real-time pricing system using a distribution capacity double auction mechanism. This project was completed in 2007 and became known as the Olympic Peninsula demonstration and serves to this day as a significant milestones in the development of transactive technology. Most of the data from that project is used in the present work and serves as the reference model for many subsequent studies in transactive control, including this one.

From about 2006 on, I had the great fortune to work with and learn from some of the best power engineers in the world, both at PNNL and as a part of my work on the Western Electric Coordinating Council's Load Modeling Task Force. I credit much of the practical knowledge I have of power systems to Jason Fuller, Frank Tuffner, and Kevin Schneider at PNNL, Clint Gerkensmeyer at Benton Rural Electric Cooperative, Dmitry Kosterev at Bonneville Power Administration, Richard Bravo at Southern California Edison, Bernie Lesieutre at the University of Wisconsin in Madison, Joe Eto at Lawrence Berkeley National Laboratory and John Undrill at the University of Arizona.

In 2009 the American Renewable and Reinvestment Act provided funding for two additional demonstrations of transactive control, one of which was managed by Steve Widergren. The AEP gridSMART demonstration project in Columbus Ohio provided the second data set for a retail capacity double auction and formalized many of the lessons learned in the Olympic Peninsula. Much of the credit for the results of that project go the large team of anonymous but outstanding engineers and operators at American Electric Power and for their fortitude and perseverance in generating an extremely valuable data set for research, for which I must offer my deepest thanks as well.

It became clear after two field trials that transactive control system implementations were too "far ahead of the headlights". I felt that it was time to step back and understand how and why this all really worked. In the fall of 2012 I applied to the University of Victoria graduate mechanical engineering program to begin pursuing this question as a PhD topic. Then quite unexpectedly, PNNL was looking for a new investment opportunity and in January 2013, PNNL dusted off an old idea I had proposed back in 2001. A new laboratory initiative called the "Control of Complex Systems" was started in April 2013, one month before I was scheduled to begin my coursework. To his credit, Suresh Baskaran placed enormous faith in our ability to sell the idea that control theory needed a new kick to meet the demands of the coming 21st Century grid, that PNNL was uniquely positioned to take on that challenge, and that DOE would soon be making a commitment to a new program in advanced controls. During the summer and fall of 2013 with support and encouragement from Marylin Quadrel and many others at PNNL I led the initiative development team from Victoria while carrying a full graduate course-load. By October 2013 the new Control of Complex Systems Initiative plan was submitted and accepted by the Laboratory. In January 2014 Jakob Stoustrup was recruited from Aalborg University in Denmark to manage the new initiative. One of Jakob's first decisions was to make transactive control the centerpiece of the new initiative. Thus it came to pass that my research on transactive control at the University of Victoria was aligned so well with the research agenda at PNNL. I am deeply grateful to the support that the Laboratory provided me during the first 3 years of this research.

But in an unexpected twist, Sila Kiliccote and Mark Hartney at SLAC National Accelerator Laboratory offered to support my research and join the new Grid Integration Systems and Mobility Group. It was an offer I could not refuse and I moved to Silicon Valley in the summer of 2016. I had the great fortune then to work with a completely new group of truly brilliant scientists and engineers, including Ram Rajagopal, Abbas El Gamal, Claudio Rivetta, Emre Can Kara, and Mayank Malik, and with the support of Arum Majumdar, the co-director of the Stanford's Precourt Institute for Energy I was able complete this work in late 2017.

Among all those who supported my efforts and influenced it the most I must acknowledge Sahand Behboodi, whose collaboration and contribution to my thinking xxviii

about the challenges we faced in completing our respective research is unmatched by anyone else. He provided a crucial combination of deep insight, broad thinking and highly disciplined approach to modeling and simulation that complement my own predilections well. Our collaboration over the years has led to the series of papers that are the basis of this dissertation and which I am optimistic will be the starting point for many years of follow-up work in this area.

I must also thank the faculty at the University of Victoria who helped me "retool" so that I would be better equipped to conduct this research. I particularly want to recognize Panajotis Agathoklis, Wu-Sheng Lu, Ben Nadler, Daniel Rondeau, Andrew Rowe, Yang Shi, and Hong-Chuan Yang, all of whom I hold in the highest regard for their consummate dedication to the craft and teaching me the finer points in the practice of their field.

I would also like to offer a special thanks Susan Walton and Pauline Shepherd of the Institute for Integrated Energy Systems for their endless patience and direct support of me and Norma over the years.

Above all, my supervisor Ned Djilali receives special recognition not only for patiently corralling my wide-ranging interests and channeling it toward a finished product, but also for encouraging me to collaborate so much with other students and faculty at UVic and elsewhere.

Finally, I cannot offer enough thanks to my family, who supported, pushed, cajoled, threatened, and otherwise assisted me in accomplishing my lifelong goal. To my wife Norma, my mother Ann, her husband Jeffry, my father John and my children Nik, Forrest and Isaac, all of whom contributed in their own way, I now offer you all an official record of the recognition you deserve for the roles you played in helping me get it done.

Whether the world is better as a result of the present work is a judgment I can only leave to others. As for myself, I am content to submit this dissertation as a record of my best attempt to heed the teachings of my forefathers...

> You are not expected to complete the task [of creation], but neither are you free to desist from trying. - R. Tarfon, Pirkei Avot

Menlo Park, 2017

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DEDICATION

To my wonderful, wise and serene wife Norma, For trustingly following me to the edge of the Earth, For confidently guiding me back when I got too close to it, For stoically supporting me when I was too weak to continue, And for lovingly walking with me through all the good times.

Chapter 1

Introduction

The National Academy of Engineering considers bulk electric power generation and distribution to be the single most important engineering achievement of the 20th century [2]. Every part of today's trans-national economy is supported in some way by electrification. A myriad power plants convert primary energy sources such as fossil and nuclear fuels, hydrological cycles, wind and solar radiation to high quality, reliable, and versatile electric energy that is used to drive an economic engine without parallel in all of human history. Arguably, not since the discovery of fire or the invention of writing has a single idea so dramatically affected every aspect of the human condition.

But the story of electricity is still being written. The 20th century model of the top-down utility and the interconnected transmission network is being challenged by 21st century problems. Climate change concerns, environmental impacts, low natural gas prices and the lack of prospective sites for large reservoirs are driving out coal plants, nuclear reactors and large-scale hydro-electric facilities as the primary sources of electric power. In many systems solar and wind resources have become an increasingly significant share of the generation resource mix.

However, with these new resources come new planning and operation problems. In particular, prime mover intermittency and the lack of control over their power output are putting strains on interconnected systems and forcing system operators to either place limits on intermittent generation resources or engage new kinds of resources in the control of the system. Over the last few decades extensive research has been conducted on how controllable loads in particular can be engaged in the various planning and operation processes in bulk power systems. Many solutions to key elements of the problem have been proposed, some of which have been successfully demonstrated in field trials, and a few of which have found their way to full-scale operation by utilities. Nearly all of these solutions utilize centralized "top-down" control methods, and most operate in an open-loop control regime. These solutions are often simple, and are demonstrably sufficient for modest levels of renewable penetration.

But centralized methods can be inflexible and lack robustness to variability and availability of both renewable supply and controllable demand resources. Decentralized control approaches are already widespread in bulk power systems, as for example in the case for regional scheduling using organized energy markets, or control area generation regulation and bulk system frequency support. Taking decentralized approaches to their logical limit, fully distributed approaches have been proposed, particularly for managing local capacity limits and under-frequency load shedding.

This thesis examines the feasibility of scaling-up to an entire interconnection a particular distributed method of integrating controllable resources called "transactive control". The problem is considered in the context of deep decarbonization of the bulk electric power systems, with particular attention to the use of loads as resources in scheduling, dispatch and regulation processes. While the problem involves regulatory, economic, and policy considerations, the main focus of this thesis is on the technical problem and solutions that support a flexible approach to regulation, economic and policy questions. This thesis proposes general methods that might be used to implement solutions that are widely applicable to the multi-scale approaches enabled by a transactive control paradigm.

Among the most important drivers in the evolution of modern elecricity infrastructure is the effect of carbon emissions on the environment. For decades we have been aware of the effect of power plant emissions on the air quality, rain water acidification, and the concentration of carbon dioxide in the atmosphere. Measures to reduce the effect of soot, nitrogen and sulfur oxides in the atmosphere downwind from fossil fueled power plants have largely been successful. Clean air policies and regulations have enabled some recovery of watersheds in the Northeast that were once suffering from acidification despite some persistent long term effect in certain ecosystems [3, 4].

The 2015 Paris climate accord had raised hopes that a global comprehensive atmospheric carbon policy was at hand, and the adoption of the Clean Power Plan by the United States was a positive sign that together with China, the world's leading economies would take effective measures to push toward effective mitigation of the impact of carbon at global temperatures rise. The recent policy reversals are widely regarded as a setback in this regard. But many consider the trend toward greater dependence on renewable resources irreversable, simply because the social, policy and market conditions increasingly favor renewable electricity generation resources [5].

Unfortunately, increasing demand for renewable electricity generation resources does not automatically bring about adoption of technologies that mitigate the climate impact of fossil-based electricity generation and satisfy ever growing electric system load. Each class of renewable generation comes with one or more disadvantages that limit the extent to which it can be integrated in bulk system operation. Hydro-electric generation has long been employed as a significant renewable source of electricity. But climate change may jeopardize the magnitude and certainty with which the existing asset base can meet demand [6, 7], while population displacement, habitat destruction and fish stock degradation limit the growth of new assets. Shifts in both load and hydro generation potentially increase uncertainty in long term planning and further enhance the need for technical approaches that support operational flexibility [8].

Similar issues arise with wind and solar generation resources. Wind power has seen rapid growth in recent years, but system reliability requirements can limit the penetration of wind generation without additional mitigation measures such as firming resources [9]. Solar resources are also becoming increasingly available but have intermittency challenges similar to those of wind. In addition, residential rooftop solar resources are challenging the classical utility revenue model [10] and are known to cause voltage control issues in distribution systems [11].

Finally, the reliable, robust control and optimal operation of an increasingly complex bulk electricity system have become very real concerns [12]. Many see 100% penetration of renewable generation as the principal objective. But this may only be possible in certain regions and only if there is a nearby bulk electricity interconnection on which such a region could rely when renewable intermittency causes shortfalls in energy supply. There are good reasons why it may not be possible for an entire interconnection to be supplied 100% by wind and solar energy, leaving open a role for nuclear, hydro, and natural gas.

The traditional utility approach to renewable intermittency is to allocate additional firm generation resources to replace all potentially non-firm renewable resources. These firm resources are often fast-responding thermal fossil resources and hydro resources when and where available. For new renewable resources the impact of this approach is quantified as an intermittency factor, which discounts the contribution of wind in addition to its capacity factor and limits the degree to which it can contribute to meeting peak demand [13]. However, the intermittency factor does not account for the ramping requirements created by potentially fast-changing renewable resources [14]. The need for fast-ramping resources discourages the dispatch of slower high-efficiency fossil and nuclear generation assets while promoting faster low-efficiency fossil and hydro, where available, for regulation and reserve services [15].

1.1 Motivation

The motivation for this thesis is two-fold. First, the long-term average cost of new renewables energy resources must be covered by the short-term price volatility in electricity markets. However, as the penetration of renewables increases, the cleared energy price is more frequently zero, or even negative as fossil-fired generators attempt to remain online while waiting for prices to rise. This decline in revenues could place an economic throttle on the growth of renewables [16] that can only be mitigated by enabling new sources for the revenues necessary to pay for utility infrastructure, particularly in the presence of high levels of distributed renewable resources. Furthermore, ramping resource scarcity may induce high price volatility in the ancillary services markets, which may lead to price shocks to the system overall. This work seeks to enable mechanisms that significantly reduce costs, stabilize prices, and enable new revenues from the coordination of the resources that support efficient system scheduling, dispatch, and regulation.

Second, although there is an existing mechanism called "transactive control" that has shown promise in field demonstrations, to date this technology has not been scaled fully to an entire interconnection. There are many reasons why this has not yet occurred, but chief among them are the obstacles to modeling, simulating and evaluating the performance of transactive systems at scale. This work seeks to identify models and methods that can be used to perform such evaluations.

Market-based mechanisms lie at the heart of transactive control systems. So deploying transactive control at the interconnection scale will require the almost ubiquitous use of markets to allocate any and all scarce resources in the systems. The long-term barrier to accomplishing such an ambitious goal is that the existing transactive system design is focused almost exclusively on the energy market-based dispatch of demand-side resources. But the value of demand response alone may be quite small [17]. The same may be said for energy storage [18]. As a result we must find other ways to provide incentives for needed resources to participate in market-based solutions. This includes markets to facilitate shifting costs (or revenues) away from (or to) non-energy markets, such as power/capacity or ramping/regulation markets. If the volume of services traded in these three markets were more balanced, then we should expect a more adaptable, equitable, and stable economic regime. Hence, through the concept of transactive control we should expect a more adaptable, equitable, and stable technical operation as well.

Thus we are motivated to understand first how a more balanced transactive system might function, second how much benefit it provides globally, and finally whether all concerned parties are better off participating in it than withdrawing from it. This thesis therefore focuses on how we model and evaluate the performance of key elements of transactive systems when operated at the interconnection scale.

1.2 Main Contributions

The first major contribution of this thesis develops and assesses the performance of a short-term demand response (DR) model for utility load control with applications to resource planning and control design. Long term demand models tend to under estimate short-term demand response when it is induced by prices. This has two important consequences. First, planning studies tend to undervalue DR and often overlook its benefits in utility demand management program development. Second, when DR is not overlooked, the open-loop DR control gain estimate may be too low. This can result in overuse of load resources, control instability and excessive price volatility. Our objective is therefore to develop a more accurate and better performing short-term demand response model. We construct the model from first principles about the nature of thermostatic load control and show that the resulting formulation corresponds exactly to the Random Utility Model employed in economics to study consumer choice.

The second major contribution of this thesis demonstrates a utility-scale direct load control problem, where the controlled loads are discrete-time zero-deadband residential thermostats that allow frequent utility-dispatched micro-adjustments to the consumer's heating/cooling setpoints. These new digital thermostats can serve as the basis for highly accurate and stable closed-loop direct load control systems, as well as price-based indirect load control systems. A new aggregate load model for discretetime zero-deadband thermostats is developed and its fundamental characteristics are described from first-principles. The third major contribution of this thesis develops an \mathcal{H}_2 -optimal power regulation scheme for balancing authorities to provide regulation services using both generation and load resources in the presence of a significant amount of intermittent renewable generation. The optimal controller is designed to minimize the loss of total economic surplus due to deviations from the schedule and dispatch resulting from system contingencies.

The fourth major contribution of this thesis considers the optimal resource dispatch problem for distribution-level resources that are sensitive to both energy and ramping prices. Resource aggregators and load-serving entities that use price-based resource control must solve an economic optimization problem to determine the optimal dispatch of distributed generation, storage, and load resources during each scheduling interval. The solution to this problem provides the basis for significant cost savings at the interconnection level.

1.3 Outline of the Thesis

The main elements of this thesis are presented in six parts. Chapter 2 introduces the challenges of including and optimizing the scheduling, dispatch, and regulation of aggregated controllable demand resources in the presence of multiple price signals from the wholesale and retail markets, and the transactive approach to solving this class of problem. Chapter 3 presents an economic model of demand response under transactive control. This model focuses on the bid behavior and price responses of the aggregate load resources that participate in retail energy markets. Chapter 4 develops a statistical model of aggregate load dynamics. The purpose of this model is to enable modeling of aggregate dynamics of loads after they receive price signals from retail energy markets. Chapter 5 examines a new control model of aggregate load and uses it to design an optimal frequency response control strategy for a control area that includes fast-acting demand response resources. Chapter 6 derives an optimal dispatch strategy and evaluates its performance under hour-ahead scheduling from wholesale markets. The strategy is developed to facilitate economically optimal dispatch when energy resources are plentiful but ramping resources are scarce. Finally, in Chapter 7 the results of these approaches are discussed and some concepts for future research are presented.

Supporting material may be found in the appendices. Appendix A and B briefly present background material on ramping price elasticity and price stability in trans-
active systems. The remaining appendices provide supporting information to assist in reproducing and building upon the results of this research. An auxiliary report is available on arXiv for those who seek background information of power system operations, demand response and transactive control [19].

Chapter 2

Problem Statement

In 2003 Economics Nobel Laureate Vernon Smith published an editorial with Lynne Kiesling in the Wall Street Journal [20] summarizing the consensus in the wake of the California Electricity crisis. In their view the crisis was in part precipitated by the lack of customer engagement in electricity pricing mechanisms [21]. Reflecting on the technical and regulatory supply-side response to the crisis, they wrote "What is inadequately discussed, let alone motivated, is the [other] option – demand response". It is now widely accepted that demand-side resources can mitigate the market power of energy suppliers. More importantly, demand response presents a real opportunity for improvement in electricity planning and operations. Research on short-term demand-side resources in particular has increased as the growth of intermittent wind and solar resources further exacerbates the problem of managing the balance between supply and demand in power systems [22].

For demand-side resources to serve as a reliable option for utilities to mitigate the renewable resources intermittency, system operators prefer to control distributed loads in real-time using strategies similar to those used for generators. This is an emerging challenge in systems where demand-side resources are expected to play a significant role in mitigating the adverse impacts of renewable intermittency on key system control functions like frequency regulation, schedule tracking, and local voltage support [23]. Transactive control was conceived as an efficient approach to integrate demand resources, as well as other distributed resources that could benefit system operations, such as rooftop photovoltaics and electric vehicle battery chargers [24, 25]. The multi-scale and multi-temporal paradigm can efficiently integrate wholesale energy, capacity, and regulation markets at the bulk system level with distribution operations, where demand response resource are aggregated and dispatched [26].

2.1 Barriers To Integrated Demand Response

Demand response has long been considered a low-cost alternative to added generation capacity [27]. Demand is now also being considered as an alternative to fast-response generation reserves to reduce the dispatch of inefficient generation resources [28]. But load control strategies for demand response applications can be challenging to plan and operate, and little has been done to quantity their economic impact at the interconnection level. This is in part because the competing objectives of local and global control [29, 30]. It is also in part because of the complexity of the models and the simplifications required to make them analytically tractable [31], numerically feasible in simulations for large-scale resource planning [32], and realizable in renewable integration studies [33].

Effective and widely used strategies for optimizing the scheduling and operation of bulk-system resources have used markets to solve the cost-minimizing securityconstrained resource allocation problem since they were proposed in the early 1980s [34]. Market-based control strategies were later adapted to building control systems [35], generalized for power balancing [36], applied to feeder-scale operations [24], then utility-scale operations [25], and most recently proposed for ancillary services [37, 38]. In addition, there is a rich literature describing models of varying complexity that have been used to study the control of aggregate loads in these cases [39, 40, 41]. The design of utility-based generation-following load control systems, either by direct command and control or by indirect price-based control, remains an active area of research.

The trend toward a more integrated and interconnected complex energy system is inexorable. Progress on the 21st century's infrastructure of complex interlocking energy resource, transformation, information, service, social, and economic networks is challenging our current understanding of these systems and our ability to design and control them. Transactive control was introduced to help address this transformation by enabling a more integrated system where all the costs of delivering energy to customers could be considered in real-time. An illustration of such a top-to-bottom restructuring of electricity delivery based on transactive control signals is shown in Figure 2.1. According to this vision of the future system, resource producers and consumers have equal access to the infrastructure provided, while operators determine the prices at which resources are efficiently allocated without violating physical limits, and aggregators group smaller resources together to balance the market power and



Figure 2.1: Top-to-bottom rethink of electricity infrastructure, including providers of transmission and distribution infrastructure, system operators and resource aggregators.

physical influence of larger resources.

Fuller defines Transactive Control as [42]

Utilizing a central control and distributed agent methodology [...] to act on behalf of consumers, sending information and automatically adjusting settings in response to a centralized signal.

To remain simple and general, this definition deliberately omits considerations of the temporal and physical hierarchies of power system operation. Neither does it specify any particular requirement to satisfy existing or anticipated challenges to the system. For example, while transactive control is widely believed to help address ramping problems, very little work has been done to show how it does so at the system level.

Recently, it seems no new work on renewable integration and demand response can fail to mention the California ISO forecast of the net load shape through the year 2020. The shape of the curve shown in Figure 2.2 has led to its colloquial name "the Duck Curve". But this genial name does not properly convey the significance of the finding: a load ramp in the late afternoon of 13,000 MW over three hours is an operational challenge that should not be underestimated. In his report on the subject, Lazar proposes ten strategies to address this challenge [43].

Strategy 1: Target energy efficiency to the hours when load ramps up sharply;

Strategy 2: Acquire and deploy peak-oriented renewable resources;



Figure 2.2: The California "Duck Curve" [Source: CAISO]

Strategy 3: Manage water and wastewater pumping loads;

- **Strategy 4:** Control electric water heaters to reduce peak demand and increase load at strategic hours;
- **Strategy 5:** Convert commercial air conditioning to ice storage or chilled-water storage;
- **Strategy 6:** Focus utility prices on the "ramping hours" to enable price-induced changes in load;
- Strategy 7: Deploy electrical energy storage in targeted locations;
- Strategy 8: Implement aggressive demand-response programs;
- **Strategy 9:** Use inter-regional power exchanges to take advantage of diversity in loads and resources; and
- **Strategy 10:** Retire inflexible generating plants with high off-peak must-run requirements.

Among these, this thesis focuses primarily on the technical mechanisms that support Strategies 4, 6, 7, 8, and 9, all of which call for a more integrated approach to system planning and operation.

Significant challenges and research opportunities remain in load modeling and simulation, understanding of the impact of consumer behavior on demand response, the foundational theory for controlling widely dispersed demand response resources, and the verification, validation, monitoring and metering of demand response systems in utility operations.

Overall, it is clear that we are entering a period of increased electric utility receptiveness and growing innovation in the methods and strategies for turning a largely passive customer base into an active part of electric system operation. Although new customer-owned distributed generation and storage resources are expected to become increasingly significant, recruitment of existing controllable loads is still the most widely available resource base available to engage the customer in system control.

The impact of controllable load on system operation can be deduced from studies on the impact of variable generation. The studies to date suggest that the benefits of variable generation outweigh the costs for reasonable mixes of variable generation relative to conventional resources [16].

Many of the adverse impacts of variable generation are positive impacts for controllable load in the sense that the magnitude of the cost or impact as a function of generator variability is a cap on the magnitude of the benefit of load as a function of load controllability.

Controllable load exhibits the further advantage of high downward substitutability and thus can be significantly favored under liberalized ancillary service markets. This feature of controllable load suggests that well-designed ancillary service markets along with market-based load control strategies could be a very powerful combination.

Significant further research on how to structure such energy and ancillary service markets, design load control strategies, and model the systems in which they operate is required to further elucidate the benefits of this approach. Ultimately our ability to plan and operate bulk power systems that utilize such resources will depend on our ability to understand both the system as a whole as well as the details of the economic, electromechanical, and human components which comprise it.

The transactive system architecture can potentially allow for the aggregation and control of all the necessary resources, both supply and demand, at every level from transmission to end-use devices, as well as all the necessary capability, energy, capac-

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ity, and ramping, at the necessary time-horizons from days-ahead to real-time. The comprehensive nature of the structure should alleviate concerns of present day system planners and operators regarding controllability of distributed smart grid assets, allowing them to be fully incorporated into system operations to achieve multiple objectives:

- Higher utilization of generation, transmission, and distribution assets, by changing on-peak load behavior;
- Lower wholesale market costs or power production costs, especially during high price periods;
- Lower ancillary service costs by engaging distributed assets to supply them;
- Lower cost for integrating new solar and wind generation into system operations by mitigating their variability and uncertainty;
- Higher environmental benefits from more efficient asset utilization and the potential to easily internalize environmental costs; and
- Increased reliability at both the bulk grid and distribution levels, from coordinating the engagement of distributed assets by multiple operating entities, by (1) increasing available reserve margins, (2) incorporating them into bulk grid wide-area control schemes, and (3) integrating them with distribution level voltage control and reconfiguration schemes.

The transactive architecture should allow increased penetration of demand response and other distributed assets, resulting from their significantly enhanced economic viability, by allowing them to provide a complete set of services on par with traditional large-scale transmission-level resources. This architecture also helps sustain utility revenue requirements, stabilizes utility customer costs at low rates made possible by lower cost distributed assets that displace the need for additional conventional infrastructure. Thus the vision of enabling overall cost effectiveness and environmentally sound grid infrastructure can be realized. While minimizing the information content of data transferred, it enhances overall cyber-security and customer privacy.



Figure 2.3: Inter-temporal data flow diagram.

2.2 Achieving Optimality in Transactive Systems

Several open questions remain when consider the optimal area control design problem in the presence of significant demand response resources that autonomously respond to frequency deviations caused by intermittent generation. Autonomous frequency control using responsive loads was proposed by Schweppe et al. [44] and demonstrated in the Olympic project, which showed its potential to mitigate generation loss. Autonomous load control can provide much faster response to frequency deviation than generation resources or dispatched load control can. However the aggregate control gain and economic elasticity of responsive loads vary over time because these loads are typically thermostatic (e.g., waterheaters, heat-pump compressors) that have both time-of-day and weather sensitivities. Thus it seems necessary to investigate how the standard ACE control or the previously considered optimal area control designs would operate in the presence of autonomous demand response.

The question of what constitutes optimality under transactive control is complicated by the lack of consensus in the definition of what is "transactive" control [45]. For this thesis we start from the definition proposed by Fuller because of its generality and simplicity. This definition does not specify any particular physical or temporal control architecture, leaving us free to choose what is most suitable for the problem at hand. We use the temporo-physical hierarchy defined in [46] as illustrated in Figure 2.3, which fits well with Fuller's definition and provides a relatively simple data flow between physical and temporal scales. Using this approach the total generation and load is scheduled hourly such that, for each control area, a uniform price is obtained at which supply is equal to load plus net exports. This schedule is used to set each area's price schedule P_S and net exports Q_S , which are in turn used by 5-minute dispatch markets [47] to allocate remaining resources in response to deviations from the hourly schedule. The allocation of Q_D additional exports at the price P_D is then used as a basis for the real-time price P_R and quantity Q_R .

Because we wish to consider the behavior of the system when demand response is active, we are motivated to find control strategies that maintain the maximum total economic surplus established by the schedule. Based on the transactive system design demonstrated by Hammerstrom et al. [48], Kiani and Annaswamy [49] proposed a hierarchical transactive control model for renewable integration that incorporates primary, secondary and tertiary frequency control that is consistent with the architecture in Figure 2.3. This model was successful in describing not only the primary regulation response of steam turbines to a loss of wind using a transactive model, but also the disequilibrium process of the secondary and tertiary responses. Because transactive control incorporates economic signals, Kiani's model can be used to evaluate the impacts of transactive controls on total economic surplus both with and without their proposed tertiary control. Evaluating the surplus impacts provides a useful alternative to the typical optimization objective of minimizing frequency deviations, generator response, or regulation cost, especially in the context of transactive controls where the joint energy, power, and ramp responses have different time-varying cost functions and are considered over different time-horizons.

The transactive control dispatch system is used to solve two concurrent problems.

(i) Schedule tracking: The hourly schedule is set by the unit commitment process [50]. From this process we obtain two important parameters that are used to dispatch retail resources at the 5 minute time-scale¹: (1) the schedule price and net exports, and (2) the participation factor for each generator and responsive load to match real-time demand and supply within a control area.

The schedule price P_s is determined from the hour-ahead supply and demand bids, and corresponds to the control area's net export schedule Q_s , which becomes the control reference for dispatching units over the coming hour.

(ii) Resource dispatch: Every five minutes generation and load resources are re-dispatched and the regulation control is reset to establish the basis for the control of system frequency and area exports over the next 5-minute interval. Units with non-zero participation factors bid into the dispatch market to allow the schedule to be adjusted so that recent resource state changes can be considered. Contribution and participation factors are computed and used (1) to reset the power output for generation units, (2) to reset the state of demand

¹The 5-minute dispatch interval is chosen because it was used in the Columbus and Olympic systems and allows for easier comparison of simulations with data obtained from operations.

response, and (3) set the frequency regulation gain for both generation and demand response.

With both the scheduling and dispatch strategies available we have all the necessary elements required to consider a regulation response strategy that minimizes schedule deviation and tracks a surplus maximizing schedule with adjustments from the last 5-minute redispatch operation. The implementation of solutions to the scheduling surplus maximization problem in the interconnection scale is addressed in [1]. According to this formulation the goal is to minimize the initial over-production of power which reduces later under-production and allows the system to track its schedule more cost-effectively.

We therefore need to address one specific aspect of the larger transactive control design problem, namely the integration of the 5-minute dispatch control with the automatic control mechanism that regulates system frequency in the presence of demand resources that are frequency sensitive [38]. To this end, this thesis proposes among other things an approach to regulating frequency and area exports, and minimizes the loss of economic surplus resulting from deviations from the hour-ahead schedule.

The approach proposed in this thesis addresses four important elements of this solution: (1) modeling aggregated demand response behavior in transactive systems, (2) controlling aggregated demand response, (3) optimal area control using demand response as a regulation resource, and (4) optimal dispatch of demand resources at the control area level.

Chapter 3

Demand Response

Historically, demand response programs have taken the form of so-called "demand side management" (DSM) activities. DSM seeks to alter electricity demand load shapes to make them better match the available supply and reduce load peaks so as to defer costly capacity expansion investments. Traditional DSM programs include increased building and appliance efficiency standards, as well as equipment replacement/retrofit programs.

In this chapter a derivation of a short-term demand response model suitable for transactive control systems is presented, followed by its validation with field demonstration data. A discussion of what the newly gained understanding of short term demand response might mean in terms of technology development, consumer acceptance, regulatory policy, and research opportunities is presented in Section 7.1.

The first contribution in this chapter is the development of an analytic function for short-term demand in residential thermostatic loads that are responsive to real-time prices. The development of the demand function reflects first principles regarding the nature of thermostatic load control. We show that this model reduces to the Random Utility Model (RUM) employed in economics to study consumer choices and the valuation of non-market goods [51].

The second contribution in this chapter is a validation of the model against data obtained from the Olympic and Columbus field demonstrations. These demonstration projects implemented residential level thermostatic inputs to a price-based market clearing transactive control system on a five minute time-scale. The results of the field demonstrations show that customers could exhibit positive short-term demand response to short-term price variations. We show that the demand model can be easily calibrated to give an accurate representation of the market data from these experiments.

Finally, the model is compared to four alternative models of demand response (DR): no DR, half DR, full DR, and demand elasticity from Faruqui's 2010 survey of DR programs [52]. For all models, we compute the error in predicting the amount of load shed at the 5-minute real-time price produced by the double-auctions of the Olympic and Columbus experiments. The results show that the RUM outperforms the alternative models for common "steady-state" demand conditions. In more extreme situations where load state diversity is low or when large price deviations occur over a very short time frame, the performance of the RUM is comparable to that of the competing models.

3.1 Background

Load shifting has long been recognized as a second approach to modulate demand response. Whereas traditional energy efficiency programs aim to reduce overall consumption, load shifting focuses specifically on changing the time of day when energy is used in order to favor times when costs are lower. Programs that focus on load shifting typically require mechanisms such as time-of-use (TOU) pricing or real-time pricing to induce transient changes in consumer behavior, such as those described by Vardakas [53]. TOU and seasonal rates focus on the customer's response to simple static price signals [54]. The Electric Power Research Institute (EPRI) carried out a major study of the top five experiments in the United States in the early 1980s and concluded that consumers indeed responded to higher prices by shifting some of their load to off-peak periods [55]. Later experiments produced similar results. The City of Anaheim Public Utilities conducted a residential dynamic pricing experiment and found that for a peak-time rebate of \$0.35/kWh they could reduce electricity use by 12% during critical-peak days [56]. California's Advanced Demand Response System pilot program used a critical peak pricing (CPP) tariff using the GoodWatts system to obtain peak reductions as high as 51% on event days with a CPP rate and 32% on non-event days with TOU rate. Enabling technology was identified as an important driver for load reductions [52]. This observation was also made in the Olympic Peninsula Project, where both TOU and real-time price (RTP) tariff were tested [57]. Similar results over a large number of studies have been widely reported and are summarized in a survey published by Faruqui et al. [52].

Since the introduction of *homeostatic utility control* by Schweppe et al. [44], it

has been understood that key system state variables such as frequency and voltage in large-scale interconnections could be regulated using price signals. Prices have since been used primarily to schedule and dispatch generation resources using power markets [50]. Both energy efficiency programs and time-of-use rates have consistently been shown to effectively reduce loads on time-scales greater than one hour [58].

To avoid unfair pricing in the presence of demand response, David et al. [59] and later Kirschen et al. [60] examined how the elasticity of demand could be considered in wholesale scheduling systems. Initial work applying market-based mechanisms to building control systems showed that the notion of market-based demand control was feasible and effective for more granular systems [35]. The general concept of transactive control was initially proposed [61, 62] as a method of coordinating very large numbers of small resources using market-like signals at the electricity distribution level. The theory is essentially the same as for wholesale markets. However, realizations can be quite different insofar as more frequently updated price signals are typically used to manage distribution system constraints such as feeder capacity limits. These prices can dispatch both distributed generation, energy storage and demand response resources at much higher temporal and physical granularity than is possible with wholesale markets.

A number of previous studies have considered the operational impact of using retail price signals for controlling load in electric power systems. Glavitsch et al [63] showed that nodal pricing could find a socially optimal operating point for power markets. Following up on this work Alvarado [64] considered the question of whether power systems could be controlled entirely using prices, and found that price signals could indeed work. But the results came with some caveats, the most significant of which is the question of stability of the feedback control over the entire system.

The feasibility of transactive control methods was demonstrated in the Olympic and Columbus projects using distribution resource control systems that dispatched distribution-level resources in quasi real-time using price signals. These experiments yielded a trove of high-resolution data about the behavior of load resources in response to short-term price variations.

Overall, two important lessons have been learned from decades of utility research, development, and field experimentation with demand response [53]:

1. Consumer interest and sustained participation is essential to the success of demand response programs. Too many programs showed too little consumer interest and participation. This drives up program costs and reduces effectiveness. Tools to keep customers engaged and responsive to utility priorities are needed. Substantive contract diversity and meaningful incentives need to be available for customers to choose and actively engage in programs.

2. Programs should not provide rewards and incentives on the basis of complex baseline or reference models. Mechanisms that provide or enable endogenous sources of counterfactual prices and quantities should be preferred by utilities.

Although transactive systems are similar to wholesale markets, the price signals are applied to different resources, affect consumer needs differently and are applied at much higher temporal and physical granularity than is possible in wholesale markets. Short-term consumer response to price variations is also understood to be quite distinct from long-term demand response. Long-term demand response is typically associated with changes in consumer behavior and the conversion to more energy efficient houses and appliances.

On the other hand, short-term demand response is primarily in the form of timeshifting and often requires automation. Short term demand response can be very different from long-term demand response because controllable load resources can be quickly exhausted, leading to control saturation. As a result, short and long term consumer responses are not generally comparable. In practice, long-term demand response models tend to underestimate the magnitude of the controllable resources and overestimate their endurance [24, 25]. This has two important consequences:(1) Planning studies tend to undervalue the potential contribution of short-term demand response system which is often overlooked in utility program development; and (2) when it is not overlooked, the open-loop control gain is underestimated, resulting in over-control, instability and excessive price volatility.

The lack of solid theoretical basis for short-term performance claims has emerged as a significant challenge [65, 28]. Using static long-term own-price elasticities can be expected to give rise to erroneous short-term demand response control because short-term elasticities are more often substitution elasticities where the substitute is obtained in time rather than by an alternative product, a distinction which was made evident by Fan's study of Australian price elasticities [66], among others. Own-price elasticities represent averages over long periods of time. These averages may fail to capture the magnitude and variability possible at any given time. For example, Reiss and White [67] developed a household electricity demand model for assessing the effects of rate structure change in California and found that a small fraction of households respond to the price changes with elasticities as large as -2, which far exceeds the average long-term elasticity of -0.14 found in Faruqui's survey of DR programs [58]. Unfortunately, computing the elasticity of demand for short-term demand response to real-time prices has proved challenging because the counterfactual price and demand are difficult to determine in the absence of a short-term feedback signal that elucidates the loads' willingness to pay [68]. Thus, more accurate models of short-term demand response are necessary for utility load control planning and design if these systems are to be deployed effectively.

3.2 Random Utility Model

Short-term consumer response to price variations is generally regarded as quite distinct from long-term demand response. The primary difference stems from the fact that long-term demand response is typically associated with enduring changes in consumer habits, whereas short-term demand response usually requires automation to support temporary changes in device behavior when prices are high. As a result, the consumer's considerations when, whether, and how to respond are not generally comparable, nor are they necessarily mutually exclusive.

Unfortunately, most studies of demand response in the electricity sector have focused on the static long-term elasticity of consumer demand [58]. Lacking alternative sources for short-term demand elasticity measures, utilities tend to use existing longterm elasticities as the basis for load control program evaluation and control systems design. Two important consequences arise from any discrepancy between the two elasticities.

- 1. Over- or underestimation of the program value. If the short-term elasticity is greater than the long-term elasticity, then an indirect load control program would tend to be under-valued and would be less likely adopted.
- 2. Over- or underestimation of control gain. If the short-term elasticity is greater than the long-term elasticity, then any attempt to mitigate instability from feedback signals would likely underestimate the open-loop control gain and would result in incorrect design of the closed-loop control system. This can potentially lead to less stable system operations and higher price volatility.

These discrepancies, and the results of the Olympic and Columbus studies showing that customers could exhibit positive short-term demand response, are the primary motivations for developing a new model of short term electricity demand.¹

3.2.1 First-principles Model

We model the general behavior of thermostats governed by consumer preference based on an engineering model of houses' responses in the short-term given a consumer's static setting for comfort. The average duty cycle is based on the fraction of time the system is *on* relative to the total cycle time. For a thermostat operating within its deadband, the fraction is very closely approximated by

$$\rho = \frac{\tau_{on}}{\tau_{on} + \tau_{off}} \tag{3.1a}$$

where

$$\tau_{on} = \frac{1}{r} \ln \frac{\tau_{set} - \frac{1}{2}\tau_{hys} - \tau_{on}}{\tau_{set} + \frac{1}{2}\tau_{hys} - \tau_{on}}$$
(3.1b)

and

$$\tau_{off} = \frac{1}{r} \ln \frac{\tau_{set} + \frac{1}{2}\tau_{hys} - \tau_{off}}{\tau_{set} - \frac{1}{2}\tau_{hys} - \tau_{off}}.$$
(3.1c)

In these equations, r is the indoor air temperature decay rate time constant, τ_{set} is the temperature set-point, τ_{hys} is the thermostat's hysteresis, τ_{on} is the steady-state temperature when the heating system is on (or cooling is off), and τ_{off} is the steadystate temperature when the heating system is off (or cooling is on). This duty cycle corresponds to the probability that we observe a device to be on at any given time.

The transactive control system assumes thermostats submit bids such that the probability of clearing a lower retail electricity price is the duty cycle required to maintain consumer comfort. Thus the system can be expected to run with the duty cycle needed while preferentially running when retail electricity prices are lower. This

¹It is worth noting that the effect of short-term demand response does not necessarily result in lower energy demand. It often results in lower peak load at the expense of increased total energy use. The reason is that consumers tend to respond to variations in price about a mean or expected price, increasing demand when prices are low and decreasing it when prices are high. Comfort is achieved by "storing" thermal resources (i.e., heat or cool) during low price periods and releasing it during high price period. Because the store/release process is not expected to be 100% efficient [69] any price-induced reduction in peak is typically associated with an increase in total energy use.

comfort tracking cost minimizing strategy is embodied in the bid-response function

$$B = \bar{P} + K \frac{\tilde{P}}{\tau_{obs} - \tau_{set}}$$
(3.2)

where \bar{P} is the expectation value for the clearing price, \tilde{P} is the standard deviation, τ_{obs} is the actual indoor air temperature, and K is the customer's comfort control setting. The consumer-controlled variable K expresses how sensitive the household is to the trade-off between money (the cost of energy) and comfort (distance from ideal temperature). A high value of K signals a higher sensitivity to price fluctuations. It gives the customer more opportunities to reduce costs at the expense of reduced short-term comfort, embodied by the thermostat's tracking error $\tau_{obs} - \tau_{set}$.

For a population of N thermostats with mean duty cycle $\bar{\rho}$, the probability of finding k devices in the on state is proportional to the binomial distribution of the count

$$g(k) = \frac{N!}{k!(N-k)!} \rho^k (1-\rho)^{N-k}.$$
(3.3)

The design of thermostatic loads requires significant oversizing of equipment, so we assume that on peak the mean duty cycle $\bar{\rho} = 0.5$. Given the mean thermostatic device load \bar{q} we can define the load deviation $Q = (k - \frac{1}{2}N)\bar{q}$ from the most probable load \bar{Q} and the total thermostatic load $Q_R = N\bar{q}$. The aggregate load entropy is then given by

$$\lim_{\rho \to 0.5} \sigma(Q) = \sigma_0 - 2\frac{Q^2}{Q_R}$$
(3.4)

where

$$\sigma_0 = \frac{Q_R}{\bar{q}} \ln \frac{Q_R}{2\bar{q}} - \frac{1}{2} \ln 2\pi$$

is the maximum entropy corresponding to the most probable load $\bar{Q} = \bar{\rho}Q_R$. The probability of observing any given load Q is the probability

$$2^{-N}g(k) = \frac{1}{1 + e^{-2\sigma(Q)}}.$$
(3.5)

Using the standard definition of demand elasticity for a load Q at price P we obtain

$$\eta = \frac{P}{Q}\frac{\partial Q}{\partial P} = P\frac{\partial \ln Q}{\partial P} = P\frac{\partial \sigma(Q)}{\partial P}.$$
(3.6)

We observe that the maximum demand responsiveness $\frac{\partial Q}{\partial P}$ occurs when the entropy

is at its maximum. Therefore at the most probable price and load it must be that

$$\frac{\partial^2 Q}{\partial P^2} \bigg|_{\substack{P = \bar{P} \\ Q = \bar{Q}}} = \frac{\partial \sigma(Q)}{\partial Q} \bigg|_{Q = \bar{Q}} = 0.$$

Integrating twice we find

$$\sigma(\bar{Q}) = a + b\bar{P}.$$

where a and b are unknown constants which must be determined from boundary conditions or from a fit to data. We substitute this result into Eq. (3.5) and deduce that the load as a function of price is

$$Q(P) = \frac{Q_R}{1 + e^{a+bP}} + Q_U$$
(3.7)

where Q_U is the unresponsive load not subject to price-responsive behavior.

3.2.2 Model Assumptions

This model has the same form as McFadden's random utility model [51]. The RUM has been used extensively in economics to study consumer choice and in the valuation of non-market goods [70]. That it can be derived independently from the first principles of thermostatic controls establishes a strong tie between the engineering approach and state of the art economic modeling of consumer preferences.²

The random utility model (and thus subsequent manipulations below) makes two important assumptions.

- 1. A consumer's choice is a discrete event in the sense that a device acting on the consumer's behalf must make an all-or-nothing decision. The consumer can either run or not run an air-conditioner. The device cannot be run at part-load for the next interval.
- 2. The consumer's (or device's) attraction to a particular choice is affected by a random error with a type 1 extreme value (Gumbel) distribution. In this case we use the term *attraction* in the retailing sense but we could just as well use the term *utility* to be consistent with economic theory. The randomness of the utility's observation of the current comfort preference is assumed to arise from

 $^{^2\}mathrm{McFadden}$ received the 2000 Nobel prize in economics for his pioneering work on economic choices.

the devices acting on behalf of consumers. The devices rationally choose the outcomes with the highest utility based on the consumer's indicated preference for comfort.

Although the random utility model has been derived using various methods, Mc-Fadden points out that according to Luce [71] it is axiomatic that the relative odds in a binary choice will remain the same for independent alternatives when additional alternatives become available. Therefore, the selection probability can always be written in the form

$$P_i \frac{e^{\nu(z_i)}}{\sum_{n=1}^N e^{\nu(z_n)}}$$

where $\nu(z)$ are scale functions of the stimulus z. When ν is linear in parameters, this result is the multinomial logit formula found in the standard statistical literature.

In the absence of prior knowledge of the quantities demanded by consumers, the derivation of the aggregate demand curve is based on this discrete choice statistic for consumer demand [72]. Thermostats act as agents on behalf of consumers whose utility is assumed to be composed of an observable component based on their comfort setting, which follows an extreme value distribution and an unobservable component that has zero mean from the perspective of the market. Thermostats are expected to bid a price that will give the heating/cooling system a probability of running satisfying the duty cycle required to maintain indoor air temperature. A thermostat's response to a market clearing price is an exclusive choice based solely on the bid it submitted [73]. For a dichotomous choice, the reasoning is as follows: U is the consumer benefit (*utility* in economic theory) that the thermostat obtains from taking a particular action given the consumer's preferences. This net benefit depends on an unobservable characteristic α that has a zero mean distribution and an observable characteristic β that is a known decreasing function of price. The net benefit is defined as $U = \beta x + \alpha$ where x is the binary choice $(x = 1 \text{ or } 0) \beta$ represent the marginal utility of the anticipated change in comfort and cost of electricity, and α represents all other unobservable variables that can give rise to error in choices. The action corresponding to x = 1 is taken if U > 0.

From a logistic regression we find that the probability of taking the action is then

$$\rho\{x\} = \frac{1}{1 + e^{-\beta x}}.$$
(3.8)

The optimal consumer bid from Eq. (3.2) is the utility maximizing price. The random



Figure 3.1: Demand curves for steady state thermostatic loads in a transactive control system.

utility model gives the same result as the load probability in Eq. (3.5).

3.2.3 Equilibrium Demand Response

The transactive control system used in the demonstration projects is quiescent when load state diversity is maximized and the total load is steady. This steady-state condition occurs when the distribution of bids is symmetric about the mean price with the same relative variance. We assume that states are uniformly distributed over the thermostat deadbands because without price disturbances, thermostatic devices follow the standard duty cycle regime. Devices will be on for the time required to rise from the on boundary of the thermostat deadband to the off boundary and off for the time required to go the other way. Undiversified states will tend to randomize under the influence of diverse physical parameters and state diversity grows until the thermostats settle into the equilibrium demand regime. After re-diversification, prices return to obeying the logistic distribution of Equation (3.8). We rescale the physical quantities for an arbitrary system with Q_U unresponsive load and Q_R responsive load at the prices p. Finally we rewrite Equation (3.8) to obtain Equation (3.7) again, where a and b are the demand curve's shape parameters.

The most probable demand elasticity at steady state occurs at maximum diversity

when $p = -\frac{a}{b}$ and

$$\hat{\eta}_D = \eta_D \left(-\frac{a}{b} \right) = \frac{a}{2} \tag{3.9}$$

as shown in Figure 3.1. Using this we can estimate the demand function parameters for any set of N bids by fitting a linear function to the bids within the central 60% of the demand response range, i.e., from $0.2Q_R$ to $0.8Q_R$. The most probable price \hat{P} is found at the mid-point $\hat{Q} = Q_U + \frac{1}{2}Q_R$. The demand elasticity $\eta_D = 2\hat{P}/Q_R d$ where d is the demand response slope obtained from the linear fit. From this we find the curve parameters

$$a = 2\eta_D$$
 and $b = -a/\hat{P}$ (3.10)

which can be obtained by applying the definition of elasticity to Eq. (3.7) such that $\eta_D = \frac{p}{Q(p)} \frac{dQ(p)}{dp}|_{p=\hat{P}}$ and observing that the most probable price occurs when p = -a/b.

3.3 Model Validation

To test the validity of the Random Utility Model, we compare its performance to that of models currently employed by utilities. The four comparator models are based on three different levels of static participation from the installed demand response capacity (i.e., 0%, 50% and 100% of $Q_R - Q_U$), as well as the -0.14 long-term demand elasticity proposed by Faruqui [58]. The key difference between the different models used by utilities is the assumption made about the short term elasticity of demand:

- 1. Zero elasticity (No DR) may be preferred when the demand response program is not expected to be a significant fraction of the total load. However, in such a case the open-loop control gain is essentially zero, and both program valuation and feedback control design are not possible. Depending on the shape of the demand curve, zero elasticity may arise at more than one quantity.
- 2. Maximum elasticity (Full DR) may be preferred when the purpose of the study is to design the feedback control so as to avoid instability. The maximum elasticity would correspond to the maximum open-loop gain and the choice of closed-loop gain would therefore be such that instability could be avoided for all physically realizable load conditions.
- 3. Most probable elasticity (Half DR) may be preferred when the purpose of the study is to evaluate a load control program's long-term value. Depending

on the shape of the demand curve, the most probable elasticity may also be the maximum elasticity.

We supplement these standard models by adding a fourth comparator:

4. Elasticity $\eta = -0.14$. This last model imposes the long term price elasticity estimated by Faruqui [58].

It can be difficult to augment these static elasticity models with what is known about consumer choices in energy purchasing. In a study by Goett and Hudson published in 2000 [74], customers were found to consider a long-term marginal energy price increase more onerous when the price is low than when it is high. However, energy consumers do not go so far as to consider price changes strictly in proportional terms either. In addition, the authors noted that bonus or coupon inducements can affect consumer choices. But these inducements are only relevant to long-term decisions such as tariff or supplier choice. Other variables often considered by consumers include contract duration (where long terms are viewed negatively), variable rates (also viewed negatively) with shorter-term fluctuations being viewed more negatively.

The demand function model proposed in Section 3.2 was validated using data obtained from the Olympic and Columbus projects. Bids received in both projects were fit using the method described above. An example of this fitting process is shown in Figure 3.2. The Olympic data set includes 103,842 market clearing events from April 1, 2006 to March 31, 2007. A total of 1,174,923 bids were received from 38 customers. Real-time prices were computed from 5-minute double auctions on a single feeder. The Columbus data set includes four separate feeders with over 5minute market clearing events from June 1, 2013 to September 30, 2013. The data for both studies is summarized in Table 3.1.

The performance of the RUM and four alternative models are evaluated by comparing the quantity predicted by each model at the observed market price to the actual quantity observed. The -0.14 long-term elasticity is unlikely to be a good approximation for fast-acting demand response, but it provides a clear indication of the errors potentially introduced when using long term elasticities in studies of short term demand response.

The results of the Olympic experiment are presented in Table 3.2. We observe that the random utility model outperforms the alternative models for all performance metrics. The difference is particularly significant for the mean error and bias error,



Figure 3.2: Example of demand function model validation with Columbus demonstration data. The bids shown are from 2013-06-22 22:45 EDT. The clearing price P_C and quantity Q_C are indicated by the circle. The expected price \bar{P} and quantity \bar{Q} are indicated by the plus sign. The standard deviation of price \tilde{P} and quantity \tilde{Q} are indicated by the ellipse.

		Demand Response			
Feeder Id	Customers	Bids	kW	(% peak load)	
Olympic (1	heating)				
_	38	$1,\!174,\!923$	$1,\!193$	(52.4)	
Columbus	(cooling)				
120	11	$281,\!045$	20	(0.7)	
140	30	699,241	45	(1.0)	
160	53	$1,\!478,\!148$	83	(1.2)	
180	8	$210,\!241$	12	(0.2)	

Table 3.1: Feeder characteristics

but less significant for the standard deviation. Results for the full Columbus data sets are presented in Table 3.3. They are mixed. We note that the Full DR model outperforms the RUM for mean error. On the other hand, the RUM outperforms the Full DR model for bias error and the standard deviation on Feeder 160 (the largest

	Erre	Standard	
Model	Mean	Bias	Deviation
Random Utility	-0.35%	1.74%	7.24%
Half DR	-0.67%	5.63%	10.10%
Full DR	-7.38%	6.83%	14.14%
No DR	6.04%	5.49%	8.89%
$\eta = -0.14$	6.62%	6.83%	14.14%

Table 3.2: Olympic data analysis results

and most diverse in terms of number of consumers). The picture that emerges out of Columbus is that the RUM model performs best in some instances but is comparable to the static models overall.

There is, however, an important qualifier to the Columbus results. Saturation of demand response (either all on or all off) is associated with diminishing load state diversity. This violates the assumption of the RUM. For this reason, we expect feeders that frequently saturate the demand response resource control to not be well represented by the RUM. These feeders would produce data more often consistent with the No DR or Full DR models (depending on conditions). Unlike the Olympic study, the experimental protocol for the Columbus study deliberately probed these limits of control every other day. This resulted in frequent loss of load state diversity in violation of the zero-mean assumption.

The experimental protocol in the Columbus demonstration is expected to have introduced additional errors. This has been verified to first order by analyzing the data excluding the experiment days. The results are shown in Table 3.4, where the error on Feeder 160 is reduced from 1.00% to 0.67%. However, a second-order effect is now observed insofar as the Full DR model seems to still perform better than the random utility model with the error reduced from 0.81% to 0.34%. This can be explained by the second-day recovery during which thermostats receive relatively lower prices compared to the previous day and tend to respond more aggressively to them. This hypothesis cannot be directly verified as the experimental protocol did not normally include a third day during which neither an experiment nor a recovery was taking place.

The model as presented is valid only for steady-state conditions. We therefore ought to consider whether transient demand response behavior influences the accuracy of the random utility model. Two factors are known to influence the magnitude of the demand response transient: (1) the fraction of devices that respond to the price

Feeder 120	Error		Standard	
Model	Mean Bias		Deviation	
Random Utility	0.78%	0.24%	0.31%	
Half DR	0.75%	0.25%	0.33%	
Full DR	0.53%	0.24%	0.30%	
No DR	0.98%	0.29%	0.37%	
$\eta = -0.14$	14.53%	0.24%	0.30%	
Feeder 140	Error		Standard	
Model	Mean Bias		Deviation	
Random Utility	0.97%	$\overline{0.29\%}$	0.36%	
Half DR	0.99%	0.33%	0.41%	
Full DR	0.71% 0.29%		0.37%	
No DR	1.27% 0.38%		0.48%	
$\eta = -0.14$	14.71%	0.29%	0.37%	
Ender 160	D		Ct and and	
Feeder 160	Err	or	Standard	
<i>Feeder 160</i> Model	Err Mean	or Bias	Standard Deviation	
Feeder 160 Model Random Utility	Err Mean 1.00%	or Bias 0.28%	Standard Deviation 0.36%	
Feeder 160 Model Random Utility Half DR	Err Mean 1.00% 1.00%	or Bias 0.28% 0.33%	Standard Deviation 0.36% 0.41%	
Feeder 160 Model Random Utility Half DR Full DR	Err Mean 1.00% 1.00% 0.81%	or Bias 0.28% 0.33% 0.31%	Standard Deviation 0.36% 0.41% 0.39%	
Feeder 160 Model Random Utility Half DR Full DR No DR	Err Mean 1.00% 1.00% 0.81% 1.19%	or Bias 0.28% 0.33% 0.31% 0.36%	Standard Deviation 0.36% 0.41% 0.39% 0.45%	
Feeder 160 Model Random Utility Half DR Full DR No DR $\eta = -0.14$	Err Mean 1.00% 1.00% 0.81% 1.19% 14.81%	or Bias 0.28% 0.33% 0.31% 0.36% 0.31%	Standard Deviation 0.36% 0.41% 0.39% 0.45% 0.39%	
Feeder 160 Model Random Utility Half DR Full DR No DR $\eta = -0.14$	Err Mean 1.00% 1.00% 0.81% 1.19% 14.81%	or Bias 0.28% 0.33% 0.31% 0.36% 0.31%	Standard Deviation 0.36% 0.41% 0.39% 0.45% 0.39%	
Feeder 160ModelRandom UtilityHalf DRFull DRNo DR $\eta = -0.14$ Feeder 180Model	Err Mean 1.00% 1.00% 0.81% 1.19% 14.81% Err Moor	or Bias 0.28% 0.33% 0.31% 0.36% 0.31% or Piece	Standard Deviation 0.36% 0.41% 0.39% 0.45% 0.39% Standard Daviation	
Feeder 160 Model Random Utility Half DR Full DR No DR $\eta = -0.14$ Feeder 180 Model	Err Mean 1.00% 1.00% 0.81% 1.19% 14.81% Err Mean	or Bias 0.28% 0.33% 0.31% 0.36% 0.31% or Bias	Standard Deviation 0.36% 0.41% 0.39% 0.45% 0.39% Standard Deviation	
Feeder 160ModelRandom UtilityHalf DRFull DRNo DR $\eta = -0.14$ Feeder 180ModelRandom Utility	Err Mean 1.00% 1.00% 0.81% 1.19% 14.81% Err Mean 0.61%	or Bias 0.28% 0.33% 0.31% 0.36% 0.31% or Bias 0.22%	Standard Deviation 0.36% 0.41% 0.39% 0.45% 0.39% Standard Deviation 0.26%	
Feeder 160 ModelRandom Utility Half DRFull DR No DR $\eta = -0.14$ Feeder 180 ModelRandom Utility Half DR	Err Mean 1.00% 1.00% 0.81% 1.19% 14.81% Err Mean 0.61% 0.44%	or Bias 0.28% 0.33% 0.31% 0.36% 0.31% or Bias 0.22% 0.18%	Standard Deviation 0.36% 0.41% 0.39% 0.45% 0.39% Standard Deviation 0.26% 0.24%	
Feeder 160 ModelRandom Utility Half DRFull DR No DR $\eta = -0.14$ Feeder 180 ModelRandom Utility Half DR Full DR	Err Mean 1.00% 1.00% 0.81% 1.19% 14.81% Err Mean 0.61% 0.44% 0.34%	or Bias 0.28% 0.33% 0.31% 0.36% 0.31% or Bias 0.22% 0.18% 0.15%	Standard Deviation 0.36% 0.41% 0.39% 0.45% 0.39% Standard Deviation 0.26% 0.24% 0.20%	
Feeder 160 ModelRandom Utility Half DRFull DRNo DR $\eta = -0.14$ Feeder 180 ModelRandom Utility Half DR Full DR No DR	$\begin{array}{c} & {\rm Err}\\ {\rm Mean}\\ \hline 1.00\%\\ 1.00\%\\ 0.81\%\\ 1.19\%\\ 14.81\%\\ \hline 14.81\%\\ \hline {\rm Err}\\ {\rm Mean}\\ \hline 0.61\%\\ 0.44\%\\ 0.34\%\\ 0.53\%\\ \end{array}$	or Bias 0.28% 0.33% 0.31% 0.36% 0.31% or Bias 0.22% 0.18% 0.15% 0.22%	Standard Deviation 0.36% 0.41% 0.39% 0.45% 0.39% Standard Deviation 0.26% 0.24% 0.20% 0.28%	

Table 3.3: Columbus analysis results for Feeders 120, 140, 160 and 180

signal, and (2) the diversity of device states when a price signal is received.

The results suggest that although the random utility model is valid for predicting steady-state demand response behavior, its accuracy is limited in the case of large magnitude price fluctuations that tend to drive a significant majority of responding devices to a single common state. This kind of state degeneracy violates the parameter distribution assumptions of the random utility model and reduces its accuracy for

Feeder 120	Error		Standard
Model	Mean	Bias	Deviation
Random Utility	0.78%	0.25%	0.31%
Half DR	0.74%	0.26%	0.33%
Full DR	0.52%	0.24%	0.30%
No DR	0.97%	0.29%	0.37%
$\eta = -0.14$	14.52%	0.24%	0.30%
Feeder 140	Error		Standard
Model	Mean	Bias	Deviation
Random Utility	0.79%	0.21%	0.26%
Half DR	0.77%	0.21%	0.28%
Full DR	0.52%	0.20%	0.26%
No DR	1.02%	0.24%	0.31%
$\eta = -0.14$	14.52%	0.20%	0.26%
Feeder 160	Err	or	Standard
<i>Feeder 160</i> Model	Err Mean	or Bias	Standard Deviation
Feeder 160 Model Random Utility	Err Mean	$\frac{\text{Bias}}{0.24\%}$	Standard Deviation 0.30%
Feeder 160 Model Random Utility Half DR	Err Mean 0.67% 0.59%	or Bias 0.24% 0.30%	Standard Deviation 0.30% 0.38%
Feeder 160 Model Random Utility Half DR Full DR	Err Mean 0.67% 0.59% 0.34%	ror Bias 0.24% 0.30% 0.28%	Standard Deviation 0.30% 0.38% 0.37%
Feeder 160 Model Random Utility Half DR Full DR No DR	Err Mean 0.67% 0.59% 0.34% 0.84%	or Bias 0.24% 0.30% 0.28% 0.33%	Standard Deviation 0.30% 0.38% 0.37% 0.42%
Feeder 160 Model Random Utility Half DR Full DR No DR $\eta = -0.14$	Err Mean 0.67% 0.59% 0.34% 0.84% 14.34%	ror Bias 0.24% 0.30% 0.28% 0.33% 0.28%	Standard Deviation 0.30% 0.38% 0.37% 0.42% 0.37%
Feeder 160 Model Random Utility Half DR Full DR No DR $\eta = -0.14$	Err Mean 0.67% 0.59% 0.34% 0.84% 14.34%	or Bias 0.24% 0.30% 0.28% 0.33% 0.28%	Standard Deviation 0.30% 0.38% 0.37% 0.42% 0.37%
Feeder 160ModelRandom UtilityHalf DRFull DRNo DR $\eta = -0.14$ Feeder 180	Err Mean 0.67% 0.59% 0.34% 0.84% 14.34% Err	ror Bias 0.24% 0.30% 0.28% 0.33% 0.28%	Standard Deviation 0.30% 0.38% 0.37% 0.42% 0.37% Standard
Feeder 160ModelRandom UtilityHalf DRFull DRNo DR $\eta = -0.14$ Feeder 180Model	Err Mean 0.67% 0.59% 0.34% 0.84% 14.34% Err Mean	ror Bias 0.24% 0.30% 0.28% 0.33% 0.28% ror Bias	Standard Deviation 0.30% 0.38% 0.37% 0.42% 0.37% Standard Deviation
Feeder 160ModelRandom UtilityHalf DRFull DRNo DR $\eta = -0.14$ Feeder 180ModelRandom Utility	Err Mean 0.67% 0.59% 0.34% 0.84% 14.34% Err Mean 0.69%	ror Bias 0.24% 0.30% 0.28% 0.33% 0.28% ror Bias 0.19%	Standard Deviation 0.30% 0.38% 0.37% 0.42% 0.37% Standard Deviation 0.22%
Feeder 160ModelRandom UtilityHalf DRFull DRNo DR $\eta = -0.14$ Feeder 180ModelRandom UtilityHalf DR	Err Mean 0.67% 0.59% 0.34% 0.84% 14.34% Err Mean 0.69% 0.58%	ror Bias 0.24% 0.30% 0.28% 0.33% 0.28% or Bias 0.19% 0.18%	Standard Deviation 0.30% 0.38% 0.37% 0.42% 0.37% Standard Deviation 0.22% 0.24%
Feeder 160ModelRandom UtilityHalf DRFull DRNo DR $\eta = -0.14$ Feeder 180ModelRandom UtilityHalf DRFull DRFull DR	Err Mean 0.67% 0.59% 0.34% 0.84% 14.34% Err Mean 0.69% 0.58% 0.45%	ror Bias 0.24% 0.30% 0.28% 0.33% 0.28% o.28% o.28% o.28% o.12%	Standard Deviation 0.30% 0.38% 0.37% 0.42% 0.37% Standard Deviation 0.22% 0.24% 0.21%
Feeder 160ModelRandom UtilityHalf DRFull DRNo DR $\eta = -0.14$ Feeder 180ModelRandom UtilityHalf DRFull DRNo DRNo DR	$\begin{array}{c} & \text{Err} \\ \text{Mean} \\ \hline 0.67\% \\ 0.59\% \\ 0.34\% \\ 0.84\% \\ 14.34\% \\ \hline 14.34\% \\ \hline \\ \text{Err} \\ \text{Mean} \\ \hline 0.69\% \\ 0.58\% \\ 0.45\% \\ 0.70\% \\ \end{array}$	ror Bias 0.24% 0.30% 0.28% 0.33% 0.28% 0.28% o.28% o.121%	$\begin{array}{c} {\rm Standard} \\ {\rm Deviation} \\ \hline 0.30\% \\ 0.38\% \\ 0.37\% \\ 0.42\% \\ 0.37\% \\ \hline 0.37\% \\ \hline \\ {\rm Standard} \\ {\rm Deviation} \\ \hline 0.22\% \\ 0.24\% \\ 0.21\% \\ 0.27\% \\ \end{array}$

Table 3.4: Columbus analysis results for only non-experiment days

predicting the load after an abrupt large-magnitude change in price is observed.

In general, we expect normal utility operations to be more like the Olympic conditions than the Columbus conditions. We thus conclude that while the Columbus results only weakly support the random utility model, they mainly point out the importance of the steady-state assumptions in Section 3.2.

3.4 Summary of Results

We have developed a logistic demand curve for short term electricity consumption derived from the first principles of controllable thermostatic electric loads operating under the transactive control paradigm. We have shown that this model corresponds to the Random Utility Model commonly used in the economics of consumer choice. The model's performance is compared to results from two US Department of Energy demonstration projects in which short-term demand response data was obtained. We find that the random utility model predicts the total demand response to smaller price fluctuations very well, but that model performance degrades as the magnitude and frequency of price excursions increases and as the diversity of load states decreases. We conclude that the random utility model is suitable for demand response studies that utilize steady state conditions for most situations with only infrequent and modest price excursions.

In its present form the random utility model provides a robust framework that is well-founded in the engineering principles of how thermostatic devices behave in price-based control environments. By joining the engineering and economic behavior of such devices, the random utility model is set to become an essential element in the planning, design and eventual deployment of large-scale load control strategies.

Chapter 4

Aggregation

This chapter proposes an aggregate load model of thermal loads controlled by thermostats that have no deadband and synchronize their control update interval to transactive market. This mechanism, which is denoted $T\Delta_0$, is used to address standard control design questions regarding the aggregate control of $T\delta_0$ thermostats in utility-scale demand response systems. Section 4.2 presents a new state-based dynamic model of the aggregate load control problem for these new types of thermostats. Section 4.3 examines the aggregate load controller design problem more generally and considers the performance various conventional load control designs using $T\delta_0$ thermostats. Section 4.4 tests the aggregate load model and controller designs using a large-scale agent-based simulation of $T\delta_0$ demand response. Further discussion of the general findings based on the simulation and suggestions for possible variations in the aggregate load controller designs are deferred to Section 7.2.

4.1 Background

Significant changes in generation mix must occur to meet growing load and mitigate the climate-change impacts of fossil-based electricity generation. Demand response control has the potential to displace some and possible all generation resources used for regulation and contingency reserves. However, the current standard practice for both direct and indirect control of thermostatic load relies primarily on so-called "oneshot" load shedding strategies for emergency peak load relief only. This approach uses a controllable subset of all thermostatic loads in a particular class, e.g., water heaters or air-conditioners, which are transitioned to a curtailed regime that reduces the population average power demand. After a time, these responsive loads are released and return to their normal operating regimes.

This strategy is known to exhibit fluctuations in aggregate load during the initial response as well as demand recovery rebounds after the loads are released. To mitigate this behavior, "one-shot" direct load control strategies are sometimes enhanced by either centralized load diversification mechanisms, such as using multiple subgroups of the responsive loads dispatched in a sequence that smooths the overall response of the load control system [75], or distributed mechanisms, such as using stochastic control strategies [76]. Many of these mechanisms require some knowledge of the aggregate thermal response of the buildings in which the loads are operating [77]. To solve the more general tracking problem where load "follows" intermittent generation [78] these mechanisms must address response saturation and loss of diversity [79], high sensitivity to modeling errors and noise [80], and stability considerations due to feedback delays [81, 82]. In particular proportional control [83] and integral control [77] strategies have been proposed to overcome many of the problems identified.

Aggregating building thermal loads are known to provide a potentially significant resource for balancing purposes [34] and have been used as the primary resource for many demand response strategies, including those that seek to use real-time prices to continuously regulate loads based on their bids, as in so-called transactive control systems. When field demonstrations of transactive control using real-time prices were conducted [24], the results sometimes revealed significant tracking errors in the discrete-time response of the aggregate load control. The cause of the error was found to be bidding strategies that didn't or couldn't account for the thermostat hysteresis. Compensated bidding strategies developed to address these problems did not fully mitigate these tracking problems [25], in part because of the complexities accounting for hysteresis. The hysteresis of standard thermostats not only requires a switchedmode representation of the individual building thermal response, but also requires so-called "refractory states", meaning that states are locked in for a certain time after being entered [84]. These locked states are associated with transition delays rather than thermal parameters. Tractable state space models of aggregate loads can be obtained using model-order reduction strategies that linearize the system model and limit the number of state variables required to represent responsive loads [39, 40], as illustrated in Figure 4.1. The rate at which devices turn on and off is determined by (1) the rate $\dot{\tau} = r_{on}$ and $\dot{\tau} = r_{off}$ at which they respectively cross the hysteresis band limits $\Delta \tau + \delta$ and $\Delta \tau - \delta$, as well as (2) the rate at which the lockout times t_{min}



Figure 4.1: State-space model of aggregate conventional thermostatic loads in heating regime with refractory states n_{on}^* and n_{off}^* . $\Delta \tau$ is the difference between the indoor and outdoor temperatures and δ is the hysteresis band limit.

expire. Such state-space models minimally represent any thermostat with non-zero deadband. However they also require model parameter identification to be used in formulating bidding strategies.

An alternative thermostatic controller design strategy was proposed to overcome these modeling issues while not compromising the advantages of hysteresis control of thermal loads [85]. This thermostat design uses a discrete-time zero-deadband $(T\delta_0)$ concept that has no refractory states and synchronizes the state transition times with external signals such as those coming from real-time retail double-auctions. The new thermostat provides significant fast-acting DR resources and the same comfort and cost savings as conventional thermostats when operated under real-time price tariffs. By using suitably selected sampling rates to limit fast-cycling of equipment, $T\delta_0$ thermostats were hypothesized to give rise to readily linearized aggregate load models. However, the aggregate control of these loads has yet to be analyzed and simulated in detail to resolve steady state control error issues and achieve utility-scale functionality.

4.2 Aggregate Load Curtailment Model

In this section we develop a model of aggregate load when using $T\delta_0$ thermostats and propose a general controller design approach that will allow various aggregate load control strategies to be explored.



Figure 4.2: General state-space model of discrete-time zero-deadband aggregate thermostatic loads.

4.2.1 Aggregate Load Model

The current standard practice for direct load control can be readily applied to discretetime thermostats when operating with zero deadband. When the sampling time t_s exceeds the minimum heating/cooling system refractory state time t_{min} we can reduce the state-space model to a second-order model as follows. Because there is no deadband we can ignore the refractory states n_{off}^* and n_{on}^* shown in Figure 4.1. We then derive the aggregate load response using a discrete-time state-transition representation for $T\delta_0$ thermostats

$$n_{on}(k+1) = (1 - \rho_{on})n_{on}(k) + \rho_{off}n_{off}(k)$$

$$n_{off}(k+1) = \rho_{on}n_{on}(k) + (1 - \rho_{off})n_{off}(k)$$
(4.1)

where k is given in units of the sampling interval t_s , and ρ_{off} is the rate at which systems move out of the off state and ρ_{on} is the rate at which they move out of the on state, which we derive from the population average properties of individual homes' thermal responses.

We can now consider a discrete-time model, as shown in Figure 4.2, where the states $x_1 = n_{on}$ and $x_2 = n_{off}$ represent the number of responsive devices in the on and off states, respectively. The time t_{min} is generally regarded to be in the range of 1 to 2 minutes, so we cannot consider designs where $t_s < 1$ minute without having to reintroduce the refractory states in the model. The rate parameters ρ_{on} and ρ_{off} represent the fraction of those devices whose indoor air temperature τ crossed the indoor temperature setpoint τ_D is any given interval t_s . The rate parameters of the discrete-time model are determined from how the thermostat setpoint threshold τ_D divides the population occupying each state. We represent the rates at which devices are added into (or removed from) the controlled device population from (or to) the general uncontrolled device population by $\mathbf{h} u(k) = \begin{bmatrix} h_1 \\ h_2 \end{bmatrix} u(k)$.

From Equation (4.1) we develop a single-input/single-output demand response system state space representation for the net change in scalar load y(k) < 0 based on the scalar load control signal u(k) > 0

$$\mathbf{x}(k+1) = \underbrace{\begin{bmatrix} 1 - \rho_{on} & \rho_{off} \\ \rho_{on} & 1 - \rho_{off} \end{bmatrix}}_{G} \mathbf{x}(k) + \mathbf{h} \ u(k)$$

$$y(k) = \mathbf{c} \ \mathbf{x}(k)$$
(4.2)

where G represents the state transition matrix for the population of thermostats, **h** represents the aggregate load control input vector and **c** represents the aggregate load output vector. In general the input vector **h** will be determined by the utility's choice of which control signals are sent to thermostats and how thermostats curtail loads. The particulars of the output matrix **c** are determined by the nature of the response that is of interest, e.g., total load reduced or increased, or net change in load.

In the case of residential thermostats, we compute the rates ρ_{off} and ρ_{on} from the population statistics of the rates r_{on} and r_{off} at which indoor air temperature deviation $\Delta \tau = \tau - \tau_D$ changes in a single home. The rates of change of temperature deviation are determined from the second-order thermal response [86]

$$q(t) = \left(\frac{C_A C_M}{U_M}\right) \ddot{\tau} + \left[C_A + C_M \left(1 + \frac{U_A}{U_M}\right)\right] \dot{\tau} + U_A \tau \tag{4.3}$$

where U_A the thermal conductance of the indoor air to the outdoor air, C_A is the heat capacity of the indoor air, U_M is the thermal conductance of the indoor air to the building's solid mass, and C_M is the heat capacity of the building's solid mass. The heat function q(t) includes both the internal, solar and ventilation heat gains and losses $q_I(t)$, as well as the heat gain or loss $q_H(t)$ resulting from operation of the heating/cooling system. From this we can derive the rates

$$r_{off}(t) = \dot{\tau}_{off} = -\frac{U_A}{C_A}\tau_A(t) - \frac{U_M}{C_A}\tau_M(t) + \frac{1}{C_A}q_I(t)$$
$$r_{on}(t) = \dot{\tau}_{on} = r_{off} + \frac{1}{C_A}q_H(t)$$

when the heating/cooling system is off and on, respectively. We assume that the heating/cooling systems are sized appropriately so that $r_{off}(t) < 0 < r_{on}(t)$ when



Figure 4.3: Discrete-time heating thermostat transition probabililities for on and off states with PDF of 10^6 homes with a setpoint change of -0.1° F.

heating and $r_{on}(t) < 0 < r_{off}(t)$ when cooling for all t. In the remainder of this chapter we will consider only the heating case, with the understanding that the cooling case is similar in every respect, with sign changes where appropriate.

The computation of ρ_{on} and ρ_{off} is illustrated in Figure 4.3. We now assume that immediately following a control action all the devices in a particular state can be inscribed in a rectangle, the horizontal dimension of which covers the range of indoor air temperatures τ and the vertical dimension of which covers the range of its derivative $r = \dot{\tau}$. The mean rates of devices during the interval k to k+1 are denoted $\bar{r}_{on}(k)$ and $\bar{r}_{off}(k)$. Device operating at the lowest rate are denoted $\bar{r}_{on}(k) - 3\sigma_{on}(k)$ and $\bar{r}_{off}(k) - 3\sigma_{off}(k)$ where $\sigma_{on}(k)$ and $\sigma_{off}(k)$ are the standard deviations of rates $r_{on}(k)$ and $r_{off}(k)$, respectively. These devices have a lower probability of crossing the setpoint threshold τ_D than ones running at the highest rates $\bar{r}_{on}(k) + 3\sigma_{on}(k)$ and $\bar{r}_{off}(k) + 3\sigma_{off}$. We assume that the distribution of devices within the rectangle has virtually zero skew and we further assume that very nearly all of the device rates in the population fall within the ranges $\bar{r} \pm 3\sigma$ for both the *on* and *off* states. The zero skew assumption may not be reasonable for large changes in setpoint, but such consideration is beyond the scope of this chapter. In addition we assume that $3\sigma < \bar{r}$ for both the *on* and *off* states, a condition which is expected to be satisfied because we assume that the devices are suitably oversized for their applications, as is the common practice.

Two distinct cases must be considered depending on whether all the faster devices cross the τ_D threshold. In the first case (shown for the *on* state in Figure 4.3) only the devices in the blue region ρ_{off} will transition to the off state. We also know that the fastest devices in the complementary mode will overshoot no further than $\tau_{off}(k+1) = \tau_D + \bar{r}_{on}(k) + 3\sigma_{on}(k)$. From this we can define the probabilities of devices transitioning out of the *off* and *on* states as

$$\rho_{off} = \frac{\bar{r}_{off}}{\bar{r}_{on} + 3\sigma_{on}} \vee 1 \quad \text{and} \quad \rho_{on} = \frac{\bar{r}_{on}}{\bar{r}_{off} + 3\sigma_{off}} \vee 1$$

respectively, where $\vee 1$ denotes the unity saturation limit for the fraction of devices that can transition from a particular state during a single time interval t_s .

In the second case (shown for the *off* state in Figure 4.3) the devices in the red region ρ_{on} will transition to the *on* state. In this fast transition case we have

$$\rho'_{off} = 1 - \frac{3 \sigma_{off}}{4 \bar{r}_{off}}$$
 and $\rho'_{on} = 1 - \frac{3 \sigma_{on}}{4 \bar{r}_{on}}$

where the different form arises from the truncation of region **B** as compared to region **A**. The choice of which value of ρ to use is based on which state has the faster devices, which can vary dramatically with outdoor air temperature and heating/cooling system performance. When $\bar{r}_{on} > \bar{r}_{off}$, then ρ'_{on} and ρ_{off} are used, and when $\bar{r}_{on} < \bar{r}_{off}$, then ρ'_{off} and ρ_{on} are used.

Note that consequently the values of ρ_{on} and ρ_{off} arise from the aggregate behavior of the populations of devices whose temperatures move at the rates r_{on} and r_{off} with variances σ_{on}^2 and σ_{off}^2 , respectively.

Parameter	\mathbf{Unit}	-3σ	Mean	$+3\sigma$
U_A	[BTU/°F.h]	200	350	500
C_A	$[BTU/^{\circ}F]$	1551	2000	2449
U_M	$[BTU/^{\circ}F.h]$	503	2000	3497
C_M	$[BTU/^{\circ}F]$	7007	10000	12994
T_S	$[^{\circ}F]$	69	72	75
Q_H	[BTU/h]	2764	11552	20340

Table 4.1: House thermal parameters.

4.2.2 Load Control Model

The basic "one-shot" load curtailment control strategy that is typically implemented by utilities can be described using Equation (4.2) with $\mathbf{h} = \begin{bmatrix} 0 \\ 1 \end{bmatrix}$ and $\mathbf{c} = \begin{bmatrix} 0 & 1 \end{bmatrix}$. Such strategies turn off u(0) devices that are on, after which we observe by how many devices the load has reduced. Given knowledge of the average kW load \bar{Q} per device, these quantities can be given in kW if desired. We obtain the pulse transfer function for the "one-shot" load curtailment when discrete-time zero-deadband thermostats are employed:

$$\frac{Y(z)}{U(z)} = \frac{(z-b)}{(z-1)(z-a)}$$
(4.4)

where $a = 1 - \rho_{off} - \rho_{on}$ and $b = 1 - \rho_{on}$. We make the following observations about this system.

- 1. The system is marginally stable. The dominant non-integrating pole is stable because $0 < \{\rho_{off}, \rho_{on}\} < 1 \implies -1 < a < 1$.
- 2. The system has a minimum-phase because $0 < \rho_{on} < 1 \implies 0 < b < 1$.
- 3. The dominant pole is always to the left of the zero because $0 < \{\rho_{off}, \rho_{on}\} < 1 \implies a < b$.

The relationship of the pole to the zero for various outdoor temperature conditions can be obtained using house thermal parameters such as the ones presented in Table 4.1. For the values of Table 4.1 the results are illustrated in Figure 4.4.



Figure 4.4: Zero and pole locations of Equation (4.4) for a random population of 1 million homes with thermal parameters given in Table IV at various outdoor air temperatures.

4.2.3 Open-Loop Response

The impulse response of the open loop system, Equation (4.4), for an impulse u(0) = 1 is :

$$y(k) = \frac{1 - b + (a - b)a^{k-2}}{1 - a} \quad \text{for } k = 1, 2, 3, \cdots$$
(4.5)

with y(0) = 0, which will always be the response of a "one-shot" load curtailment signal when the loads are controlled by discrete-time thermostats with no deadband.

The steady state response is

$$y(\infty) = \frac{\rho_{on}}{\rho_{off} + \rho_{on}}$$

which we observe is the population average duty cycle R and is independent of u(k) for k > 0 provided that $\sum_{j=0}^{\infty} u(j) > 0$. We also note that any signal u(k) > 0 will add more devices to the controlled population while u(k) < 0 will remove devices from the controlled population. For any k > 0 we only require $u(k) = -\sum_{j=0}^{k-1} u(j)$


Figure 4.5: Open loop impulse (left), decay (center), and step (right) response of aggregate load model compared to agent-based simulation for 100,000 thermostats per unit input u at -10°C.

to return to the initial condition $\mathbf{x}(0)$ and when $\sum_{j=0}^{\infty} u(j) = 0$, we will always have $y(\infty) = \mathbf{c}\mathbf{x}(0)$. The model responses to various inputs are compared to simulations with 100,000 thermostats using an agent-based simulation. The results illustrated in Figure 4.5.

4.2.4 Model Identification

The performance of a utility-scale implementation of aggregate load controllers to be designed in the next section depends on the estimation accuracy of model parameters ρ_{on} and ρ_{off} . Values for these parameters can be obtained by comparing the response to an impulse input with Equation (4.5). We can show that the responses at k = 2 and 3 are sufficient to give an estimate for the observer parameters.

A single impulse response can be used to provide a relatively quick and simple method of model parameter identification. After a single impulse u(0) and initial conditions $\hat{\mathbf{x}}(0) = \begin{bmatrix} 0 \\ 0 \end{bmatrix}$, the system's initial response is observed to be $\hat{\mathbf{x}}(1) = \begin{bmatrix} 0 \\ y(1) \end{bmatrix}$. After a second time-step, the system is observed to be in the state $\hat{\mathbf{x}}(2) = \begin{bmatrix} x_1(2) \\ y(2) \end{bmatrix}$. Given Equation (4.1) we can estimate

$$\hat{\rho}_{off} = 1 - \frac{y(2)}{u(0)}$$

and similarly after a third observation y(3) is obtained we estimate

$$\hat{\rho}_{on} = \frac{y(3) - \frac{[y(2)]^2}{u(0)}}{u(0) - y(2)},$$

This method of estimating the model parameters makes two assumptions that must be considered:

- 1. The initial conditions are $\hat{\mathbf{x}}(0) = \mathbf{0}$. This condition is achieved by releasing all the devices currently under control and waiting for the normal settling time of controlled devices to elapse to ensure that the uncontrolled population is roughly in both state and thermal equilibrium.
- 2. Only a single control impulse u(0) is sent at time k = 0 and then no control signals u(k) for $k = 1, 2, 3, \cdots$ are sent so the impulse response can be clearly discerned in the outputs y(2) and y(3).

These conditions are relatively easy to create and the impulse u(0) need not be large to obtain useful measurements, particularly if the test is repeated multiple times for each outdoor air temperature. Using this method a database of model parameters can be obtained and used to estimate model statistics as well. Furthermore, the magnitude y(1) will give an estimate of the product **hc**, while observation of y(4)permits the estimation of **h** and **c** separately, if needed.

Finally, it is not necessary to probe the system response at all outdoor conditions because the relationship of a and b is well known, particularly for infrequent peak load conditions that can be more difficult to observe. The linear relationship of aand b over the range of low outdoor air temperatures is seen in Figure 4.4 and allows reliable extrapolation from more frequent conditions to more rarely observed and more critical peak load conditions.

In the likely case that measurement noise is present, a mean square approximation of these parameters may be considered by producing a series of impulses spaced apart by a sufficient interval to guarantee that Assumption (1) above is satisfied. Under high duty-cycle conditions, the linear relationship of the zero and pole assures that varying conditions are not an obstacle to determining the slope of the line that relates them using a least-squares fit.

4.3 Aggregate Demand Response Controller Design

In the previous section we proposed an aggregate load model and discussed its main open-loop properties. It is important to this study that we examine the typical range of control strategies suited to direct dispatch of demand response resources and assess the degree to which these strategies work satisfactorily for aggregations of $T\delta_0$ thermostats. Therefore, in this section we examine various controller designs, all of which are variations implemented on the general controller design shown in Figure 4.6. The controller design parameters for this general controller are as follows:

- **h** is the system input vector for the response to the scalar signal u(k). This is generally a curtailment signal and indicates how many devices are turned *off*.
- c is the system output vector for the scalar load y(k) arising from the internal states $\mathbf{x}(k)$.
- $\tilde{\mathbf{h}}$ is the observer input vector.
- $\mathbf{\tilde{c}}$ is the observer output vector.
- h is the scalar reference input gain.
- \mathbf{K}_c is the observer gain vector.
- K_q is the integral error feedback gain scalar.

The flexible design of controller allows for many of the basic control strategies that are typically employed for discrete-time linear time-invariant system. This is done with the understanding that some of the parameters may change over time intervals much longer than the time horizon over which most demand response control objectives are stipulated. In particular it is expected that the state transition rates ρ_{on} and ρ_{off} will change as a function of outdoor air temperature, but that the relationship will be relatively easy to obtain for the aggregate population and that it will be sufficiently consistent between seasons to allow simple system identification approaches to provide accurate long term model parameters. A simple method of identifying these parameters was discussed in the previous section.



Figure 4.6: General structure of the controller (top): Block (A) is the aggregate load model, (B) is the reduced-order observer, (C) is the load controller, and (D) is the integral error feedback.

	(Observer	Controll	Error feedback	
Configuration	ñ	õ	K_c	h	K_q
Proportional	$\begin{bmatrix} 0\\ 0\end{bmatrix}$	$\begin{bmatrix} 0 & 1 \end{bmatrix}$			
$\begin{bmatrix} 0 & \rho_{on} + \frac{1}{2}\rho_{off} \end{bmatrix}$	0	$\rho_{on} + \frac{1}{2}\rho_{off}$			
Unity damping	$\begin{bmatrix} 1\\ 0\end{bmatrix}$	$\begin{bmatrix} 0 & 1 \end{bmatrix}$	$\begin{bmatrix} \hat{\rho}_{on} & 1 - \hat{\rho}_{on} - \hat{\rho}_{off} \end{bmatrix}$	$1 - \hat{\rho}_{on} - \hat{\rho}_{off}$	0
Deadbeat	$\begin{bmatrix} 1 \\ 0 \end{bmatrix}$	$\begin{bmatrix} -1 & 1 \end{bmatrix}$	See Eq. (4.7)	See Eq. (4.8)	0
Pole placement	$\begin{bmatrix} 1 \\ 0 \end{bmatrix}$	$\begin{bmatrix} -1 & 1 \end{bmatrix}$	See Eq. (4.9)	See Eq. (4.10)	0
Integral error feedback	$\begin{bmatrix} 1\\ 0\end{bmatrix}$	$\begin{bmatrix} -1 & 1 \end{bmatrix}$	See Eq. (4.11)	See Eq. (4.12)	See Eq. (4.11)
					1

Table 4.2: Controller design configurations.



Figure 4.7: Discrete-time root-locus of aggregate $T\delta_0$ thermostatic loads.

4.3.1 Proportional Control

We can now consider the behavior of proportional control by examining the root locus of the closed-loop system. With -1 < a < b < 1, the root-locus in Figure 4.7 indicates that the system has two real poles and a zero that is always between the poles.

Since the open-loop system in Equation (4.4) has a discrete integrator, the steady state error for a step input is zero. Unfortunately, numerical methods do not find

Temperature	Load	Gain	Zero	Dominant pole	Gain margin
$[^{\circ}C]$	[% peak]	K	[/h]	[/h]	[dB]
-15	79	0.45	0.78	0.93	3.1
-10	70	0.40	0.66	0.91	3.9
-5	61	0.20	0.49	0.93	11.1
0	33	0.70	0.30	0.65	0.8
5	25	0.80	0.27	0.56	0.3
10	17	0.85	0.26	0.49	0.6
15	10	0.90	0.24	0.41	0.6

Table 4.3: Maximum attenuating proportional control gains for various conditions.

values of K with acceptable phase and gain margins. However, gains can be found for the fastest possible attenuation for various outdoor conditions, as shown in Table 4.3.

The Jury-Marden test gives us the stability constraint on the closed-loop gain

$$\rho_{on} < K < \rho_{off} + \rho_{on}$$

which can be a very narrow range and highly dependent on accurate knowledge of the value of ρ_{on} , particularly when ρ_{off} is small. Small values of K may lead to slow response under certain conditions. PID control can yield a stable aggregate load controller under conditions we expect to encounter in a realistic utility operational setting. However, the response can also be somewhat oscillatory under higher load conditions, when both fast and reliable aggregate load control is most needed, as shown in Figure 4.8 (left). The narrow band of constraints on K limit at high loading conditions limits the possibility of improving performance to such an extent that proportional control seems largely impractical for direct load control. Indeed at peak load only marginally stable control can be achieved when $K = \rho_{on}$.

4.3.2 Proportional-Derivative Control

Faster response than proportional control is often achieved by using a proportional derivative controller such that

$$G_{pd}(z) = \frac{(z-b)(k_1z+k_2)}{(z-1)(z-a)}$$



Figure 4.8: 100 MW proportional load control step response with maximum attenuating proportional control gains based on the load parameters in Table 4.1 (left) and proportional-derivative control step response (right).

T_O	k_1	k_d	z_1	z_2	p_1	p_2
-15	9.94	4.38	0.78	-0.44	0.80	-0.40
-10	9.95	4.38	0.66	-0.44	0.68	-0.41
-5	9.95	4.38	0.49	-0.44	0.54	-0.42
0	10.52	4.63	-0.44	0.30	-0.38	0.33
5	10.66	4.69	-0.44	0.27	-0.36	0.30
10	10.77	4.74	-0.44	0.26	-0.35	0.27
15	10.87	4.79	-0.44	0.24	-0.33	0.25

Table 4.4: Proportional-derivative controller design parameters.

Solving for the fastest possible response with zero poles we obtain

$$k_1 = \frac{a}{b^2} - \frac{a}{b} - \frac{1}{b}$$
 and $k_2 = \frac{a}{b}$

However, the stability margin of the system is not suitable for operation in noisy conditions.

Using pole placement for damping $\xi = 0.8$ and settling time $t_s = 1$ hour, as shown in Table 4.4, does not offer improvements in the system's stability characteristics in spite of satisfactory time-domain response to step inputs, as shown in Figure 4.8 (right).

Lead and/or lag compensator design for the wide variety of conditions that the controller is required to operate under would require an adaptive controller and was not considered here.

4.3.3 Unity Damped Control

We can design a direct aggregate load control strategy for $T\delta_0$ thermostats that will maintain a constant desired load curtailment r(k) > 0 for k > 0, assuming that y(0) = r(0) = 0. We desire only that

$$y(k) = r(k)$$
 for $k = 1, 2, 3, \cdots$

which gives us

$$u(k) = (\mathbf{ch})^{-1}[y(k) - r(k) + \mathbf{c}(\mathbf{I} - \mathbf{G})\hat{\mathbf{x}}(k)]$$
 for $k = 1, 2, 3, \cdots$

where **G** is the state transition matrix for the population of thermostats and $\hat{\mathbf{x}}(k)$ is an estimate of $\mathbf{x}(k)$.

For any curtailment control system the accumulated inputs from u(0) to u(k-1)represents the total number of devices N that have been curtailed up to the time k. So $\hat{x}_2(k) = y(k)$ represents the load that is still off at the time k. Therefore we must have

$$\hat{x}_1(k) = \sum_{j=0}^{k-1} u(j) - y(k) \text{ for } k = 1, 2, 3, \cdots,$$

which represents the load that has returned to the on state at the time k. This gives us the estimated state

$$\hat{\mathbf{x}}(k) = \begin{bmatrix} \sum_{j=0}^{k-1} u(j) - y(k) \\ y(k) \end{bmatrix}$$
 for $k = 1, 2, 3, \cdots$

This state can be found from the input u(k) and output y(k) using a reduced order observer described by:

$$\hat{\mathbf{x}}(k) = \tilde{\mathbf{b}} \sum_{j=0}^{k} bu(k) + \tilde{\mathbf{c}} y(k) \text{ for } k = 1, 2, 3, \cdots$$



Figure 4.9: Unity damped system diagram.



Figure 4.10: Unity damped (left) and deadbeat (right) responses of aggregate load controllers.

where $\tilde{\mathbf{b}} = \begin{bmatrix} 0\\1 \end{bmatrix}$ and $\tilde{\mathbf{c}} = \begin{bmatrix} 1\\-1 \end{bmatrix}$. From this we can determine the load control signal:

$$u(k) = r(k) - \hat{a}y(k) - (1 - \hat{b}) \sum_{j=0}^{k-1} u(j) \quad \text{for } k = 1, 2, 3, \cdots,$$
(4.6)

where $\hat{a} = (1 - \hat{\rho}_{off} - \hat{\rho}_{on})$ and $\hat{b} = 1 - \hat{\rho}_{on}$ with $\hat{\rho}_{off}$ and $\hat{\rho}_{on}$ being the estimates of the aggregate load response. This controller can be implemented as shown in Figure 4.9 with $\hat{c} = \frac{1}{1 + \hat{\rho}_{on}}$ and $\hat{d} = \frac{\hat{\rho}_{on}}{1 + \hat{\rho}_{on}}$. We observe that $0 < \hat{d} < 0.5 < \hat{c} < 1$. Thus the added pole is stable and the added zero does not affect the minimum phase property of the system. We note that this controller should reach steady state on the first iteration and thus has a damping ratio of 1.0 and settling time of t_s , as shown in Figure 4.10 (left).

The introduction into the system of model parameters \hat{c} and \hat{d} creates a source of constant disturbances in the system that can result in a steady state error. This problem limits general applicability of this controller design unless integral error feedback control is used. An alternative approach to mitigate model error is to include information obtained directly from controllable devices. This would be the case if bidding mechanisms are used, such as when retail markets are implemented using double auctions [36, 24, 25].

4.3.4 Deadbeat Control

An alternative type of controller is a deadbeat controller that uses only two load control impulses to achieve steady state [87]. The controller has the advantage that it does not continually draw on the uncontrolled population of devices to achieve the control objective. It has the disadvantage that it may overshoot on the second time-step, as shown in Figure 4.10 (right).

The state $\hat{\mathbf{x}}(k)$ and output y(k) are determined using the matrices

$$\tilde{\mathbf{h}} = \begin{bmatrix} \frac{(1-\hat{b})z}{z-1} \\ 0 \end{bmatrix} \quad \text{and} \quad \tilde{\mathbf{c}} = \begin{bmatrix} 0 \\ \hat{a} \end{bmatrix}$$

We solve for the feedback gain for zero poles using

$$\mathbf{K} = \begin{bmatrix} \hat{a} + 1 & -\hat{a} \end{bmatrix} \tilde{\mathbf{A}}^{-T} \mathbf{C}^{-1}$$
(4.7)

where $\tilde{\mathbf{A}} = \begin{bmatrix} 1 & 0 \\ \hat{\rho}_{on} + \hat{\rho}_{off} - 2 & 1 \end{bmatrix}$ is a Toeplitz matrix and $\mathbf{C} = \begin{bmatrix} 0 & \hat{\rho}_{off} \\ 1 & 1 - \hat{\rho}_{off} \end{bmatrix}$ is the controllability matrix. The tracking reference input gain is

$$h = \frac{1}{\mathbf{c}(\mathbf{I} - \mathbf{A} + \mathbf{h}\mathbf{K})^{-1}\mathbf{h}}$$
(4.8)

4.3.5 Pole Placement Control

In the general case of a pole-placement controller [87], we have the same controllability matrix and Toeplitz matrix as the deadbeat controller above. Given a desired damping coefficient ξ and settling time t we compute the desired pole locations z_1 and z_2 and we obtain the tuned controller gains

$$K_{c} = \begin{bmatrix} \hat{\rho}_{on} [\hat{\rho}_{off} + \hat{\rho}_{on} (1 + z_{1} + z_{2})] + z_{1} z_{2} - z_{1} - z_{2} - 1 \\ -\hat{\rho}_{off} - \hat{\rho}_{on} - z_{1} - z_{2} \end{bmatrix}^{T}$$
(4.9)

$$h = \frac{z_1 z_2 - z_1 - z_2 - 1}{\hat{\rho}_{on}} \tag{4.10}$$

As in the case of unity-damped and deadbeat controllers, any error in $\hat{\rho}_{on}$ and $\hat{\rho}_{off}$ is expected to result in a steady state error.

The performance of the five different controllers discussed in this section depends on the accuracy of the estimated system parameters ρ_{on} and ρ_{off} . If these are not sufficiently accurate, this may lead to unacceptably large steady-state errors. Assuming that the values of the system parameters change more slowly than the time constants of the system, steady-state error can be mitigated using an integral error feedback controller. The design of such a controller is discussed next.

4.3.6 Integral Error Feedback

To correct for the steady state error in the pole-placement controller we implement integral error feedback using an augmented state

$$q(k+1) = q(k) + t_s[r(k) - y(k)].$$

We include the integral feedback error in the state-space representation using the augmented controllability matrix

$$\mathbf{C} = \begin{bmatrix} 0 & \rho_{off} & 0 \\ 1 & 1 - \rho_{off} & 0 \\ 0 & -t_s & 1 \end{bmatrix}$$

and the characteristic polynomial is $a(z) = (z - 1)^2(z - a)$ or

$$a(z) = z^{3} - (a+2)z^{2} + (2a+1)z - a$$

The augmented Toeplitz matrix is therefore

$$\tilde{\mathbf{A}} = \begin{bmatrix} 1 & 0 & 0 \\ \rho_{off} + \rho_{on} - 3 & 1 & 0 \\ 2\rho_{off} + 2\hat{\rho}_{on} - 3 & \rho_{off} + \rho_{on} - 3 & 1 \end{bmatrix}.$$

The desired characteristic polynomial is simply $\alpha(z) = (z - z_1)(z - z_2)(z - z_q)$

and

where z_1, z_2 , and z_q are the desired poles of the closed-loop system. Thus we have

$$\alpha(z) = z^3 - (z_1 + z_2 + z_q)z^2 + (z_1z_2 + z_1z_q + z_2z_1)z - (z_1z_2z_q)$$

from which we obtain controller gains based on the estimated model

$$\begin{bmatrix} \mathbf{K}_{c} & K_{q} \end{bmatrix} = \begin{bmatrix} \hat{\rho}_{on} + \hat{\rho}_{off} - 3 - z_{1} - z_{2} - z_{q} \\ z_{1}z_{2} + z_{1}z_{q} + z_{2}z_{q} - 3 + 2\hat{\rho}_{on} + 2\hat{\rho}_{off} \\ 1 - \hat{\rho}_{on} - \hat{\rho}_{off} - z_{1}z_{2}z_{q} \end{bmatrix}^{T} \tilde{\mathbf{A}}^{-T} \mathbf{C}^{-1}$$
(4.11)

with the reference input gain

$$h = \frac{1}{z_1 z_2 + z_1 z_q + z_2 z_q + 2\hat{\rho}_{on} + \hat{\rho}_{off} - 3}$$
(4.12)

This control design eliminates the steady-state error induced by model errors in $\hat{\rho}_{on}$ and $\hat{\rho}_{off}$ with a settling time determined by the pole z_q .

4.4 Agent-based Simulation Results

The controller designs were tested on an agent-based simulation [88] of 100,000 residential thermostats using a second-order building thermal model, including internal and solar gains, and ventilation losses. (The thermal properties of these loads are given in Table C.1.) The second order models are linearized for the given outdoor temperature resulting in first-order models for each house such that the individual homes have distinct air temperature change rates as a function of the state of the heating system. Note that the thermal model used in the agent-based simulation presented in this section is not an aggregate model as the one used for controller design in the previous section. This allows the performance of the controllers designed in the previous section to be evaluated using a plant model which better reflects reality. Therefore, the effects of disturbances caused by errors arising from model order reduction of the design model as well as measurement noise are considered. The results of the PDF model estimates are given in Table D.1.

To implement direct load control, thermostat setpoint changes are applied to a subset of uncurtailed heating units. The magnitude of the setpoint change is generally a function of the fastest rate of change, which at peak load is approximately r_{off} . The magnitude of this value was chosen to ensure that the impulse response resulted

Control	Poles	Gains			Errors	
		K_c	K_q	h	Average	Maximum
Impulse	[0]	[0.00 0.00]	0.09	0.00	69%	71%
Proportional	[0]	[0.00 0.31]	0.09	0.31	44%	87%
Damped	[0.72]	[0.09 0.46]	0.09	0.91	18%	61%
Deadbeat	[0.72]	[0.28 1.46]	0.09	2.93	35%	40%
Pole placement	[0.43]	[0.60 0.59]	0.09	3.67	84%	92%
Integral	$\begin{bmatrix} 0 & 0.72 \end{bmatrix}$	$\begin{bmatrix} -0.30 & 1.61 \end{bmatrix}$	0.09	1.00	13%	41%

Table 4.5: Controller design parameters for peak load $(-15^{\circ}C)$.

in a 100% response at the first time step. The number of homes curtailed is based on the average heating system load when on such that u(k) = 1 is equivalent to 1 MW of load, or approximately $N_C = 10^6/\bar{Q}$, where \bar{Q} is the mean value of the heating unit load $Q = q_H/COP$, where COP is the heating unit efficiency.

When a negative value of u(k) is obtained, units are released into the uncurtailed population. The simulation first releases systems that have been curtailed the longest, ensuring that the released population is the most diversified and exhibits the least rebound oscillation after returning to the uncurtailed population.

The controller design parameters discussed in Section 4.3 are generated for peak load conditions using the thermal parameters shown in Table 4.1. A summary of the controller design parameters studied are shown in Table 4.5.

The impulse response for $\tau_O = -15^{\circ}$ C is shown in Figure 4.11 (left). The response is different from the one expected from the aggregate model and illustrates the effect of the errors and noise induced by state fluctuations in the system which are not captured by the second-order aggregate load model. Further, the steady-state of the response and the settling time for the devices to reach their normal diversity are also indicated. The proportional control response does not have a steady state error, but this is not clearly visible because of the very slow response, as shown in Figure 4.11 (right).

The response of the unity damping controller is shown in Figure 4.12 (left). The effect of model error can be seen in the initial response, as a result of which it fails to quickly achieve the desired level of curtailment. The response of deadbeat control has the expected significant overshoot, but also exhibits large steady state error, as shown in Figure 4.12 (right).

The response of the tuned controller using pole placement shows a compromise



Figure 4.11: 100 MW impulse response (left) and proportional control (right) at -15° C.



Figure 4.12: 100 MW unity damping load control (left) and deadbeat load control (right) at -15° C.

between the unity damping and deadbeat controller designs, but still exhibits a large steady state error, as shown in Figure 4.13 (left). The integral error feedback control response shown in Figure 4.13 (right) addresses the problems identified in the previous controller designs. The system exhibits an acceptable level of overshoot and maintains the desired curtailment level for more than 90 minutes.



Figure 4.13: 100 MW tuned load control (left) and integral feedback control (right) at -15° C.

4.5 Summary of Results

In this chapter we considered the utility-scale direct load control problem for the situation when the controlled loads employ discrete-time zero-deadband $(T\delta_0)$ residential thermostats. We have shown how $T\delta_0$ thermostats allow utility dispatchers to use small adjustments to the consumer's setpoint to modulate the total load with greater precision and endurance than typically possible using current setback control of thermostats with non-zero deadbands. These new digital thermostats can serve as the basis for highly accurate direct load control systems, as well as price-based indirect load control systems.

We have derived a new linear aggregate load model based on the dynamics of load states and used its fundamental characteristics to considers a number of benchmark aggregate load control designs from first-principles. We used this model to design a simple closed-loop aggregate controller for a discrete-time utility-scale demand response dispatch system that is compatible with the requirements for both direct and indirect load control systems and tested the control design using a large-scale agentbased model of demand response based on thermostatic loads. We showed that the aggregate controlled load is stable, controllable and observable and exhibits both the transient and steady-state response characteristics necessary to serve equally well for utilities that seek to control load using either direct load control or price-based indirect demand response strategies.

Chapter 5

Regulation

Under the transactive control paradigm, retail markets for energy, capacity, and regulation services are deployed to provide an analogous realization of wholesale markets at the distribution level. In spite of the conceptual similarity, the behavior of retail markets differs significantly from that of wholesale markets and remains an active area of research [89]. In particular, load behavior usually dominates the behavior of retail systems, which contrasts with wholesale systems where generation is dominant. In addition, there are a number of important processes in bulk power interconnection operations that have yet to be integrated fully into the transactive paradigm. Two such processes are system frequency regulation and control area import/export schedule tracking.

In Section 5.1 we introduce the interconnection operation control platform. We then present the methodology for optimally controlling an area's response to system frequency deviations while tracking scheduled area exports. In Section 5.2 we propose the structure of the model and the design solution for an optimal area control policy. Finally in Section 5.3 we evaluate the performance of the optimal control policy when compared to the conventional control policy under varying demand response conditions.

5.1 Methodology

System operators that wish to use demand response resources to mitigate renewable intermittency must have the means to control responsive loads in much the same way they control responsive generating units. This can be done by updating the load control system gains every few minutes given the available demand response resources committed to frequency regulation. Given these load control gain settings, the loads' responses to frequency deviations can be autonomous without requiring the use of an analog to AGC for loads.

It is quite feasible with today's technology to dispatch load control gain settings to load aggregators who then disseminate specific setpoints to the loads they control without having to dispatch AGC signals to each load directly. However, doing so requires adjustments to the existing frequency and inter-area power exchange control system. This section details how this is accomplished within the structure of modern power system control.

5.1.1 Frequency control mechanism

Primary control of bulk electric power systems is driven in part by deviations in frequency at the system level and modeled by the system transfer function $\frac{1}{Ms+D}$, where M represents the system's inertial response and D represent the system's damping response. Each control area implements a combination of speed-droop control on conventional generating units, under-frequency load shedding, and grid-friendly loads to provide primary control. Renewable generating units provide no frequency regulation capability because they cannot control their prime movers (wind and solar). Secondary control of frequency and area exports is provided by units equipped with master controllers and is based on the area control signal a using the conventional ACE formula

$$A(t) = \Delta Q(t) + B\Delta f(t), \qquad (5.1)$$

where A(t) is the raw ACE signal, $\Delta Q(t) = Q(t) - Q_s$ is the deviation of the net energy exported from the scheduled net exports over the lines and $\Delta f(t) = f(t) - f_s$ is the interconnection's frequency deviation from scheduled frequency. If an area's net exports deviates from its schedule (because of either an internal or external disturbance), the area adjusts its generation (and potentially also its load) such that it eventually will zero out A(t), while also providing adjustments necessary to support system-wide corrections to frequency deviation.

In most realizations the ACE signal is updated by the SCADA system about every 4 seconds and further passed through a smoothing filter so that it changes with a timeconstant well in excess of the generating units' fastest response, e.g., 30-90 seconds, with the purpose of reducing wear and tear on generating unit governor motors and



Figure 5.1: System frequency control diagram.

turbine valves [90]. In addition, this control action is subject to control performance standards (i.e., CPS-1 and CPS-2 [91]), although these are not considered in this study.

The fast response of frequency-sensitive loads (grid-friendly smart appliances) to the frequency deviation enables the grid operator to redispatch generating units in a more economically-efficient manner, although demand response may saturate relatively quickly. Figure 5.1 illustrates the system's frequency regulation diagram with variable renewable generation and frequency sensitive demand response.

5.1.2 Transactive control platform

As noted in Chapter 2, Fuller's definition of Transactive Control does not specify any particular physical or temporal control architecture. We chose the hierarchy illustrated in Figure 2.3 because it provides a relatively simple data flow between physical and temporal scales. Using this approach, the total generation and load is scheduled hourly such that for each control area a uniform price is obtained at which supply is equal to load plus net exports. Figure 5.2 illustrates an interconnection including N wholesale markets each belongs to a control area that exchange electricity through system tielines to increase the economic surplus. This schedule is used to set each area's price P_s and net exports Q_s which are in turn used by 5-minute dispatch markets [24] to reallocate resources in response to deviations from the hourly schedule. Depending on the events that have occurred during the preceding 5-minute time period, the state of operation of generators and loads at the end of the period is not necessarily the same as at the beginning of the period. For example, the water



Figure 5.2: Inter-area transfer flows within an interconnected system consisting of N control areas.

temperature of a hot water tank whose heater was switched off at the last time period has lowered, and we expect this load might submit a higher bid to the market to avoid staying in the off mode and satisfy a higher level of demand urgency. Accordingly, generation and load resources may participate in the market with new bid prices, and as a result the clearing price P_D would change. However, the area export e_a should remain as close as possible to the hourly schedule.

5.1.3 Demand response integration in the 5-minute market

Figure 5.3 illustrates the impact of a supply disturbance on the 5-minute market settlement process. The blue and the red dashed curves represent the demand and the supply curves, respectively, in the next market cycle. In this example a portion of renewable generation (in the flat segment of supply curve) is lost and the supply curve is shifted to left by the magnitude of the disturbance ΔQ_s^{-1} . Load participation in

¹Other kinds of disturbances include non-renewable generation loss or changes in load, and these will have similar impact with only particular details differing. The choice of renewable generation loss is preferred in this study because (1) it is a common concern for which demand response is



Figure 5.3: Five-minute resource dispatch with supply (red) and demand (blue) response to a loss of generation (ΔQ_s) .

frequency response prior to the redispatch operation causes the shape of the demand curve to change slightly and present only the remaining available demand response to the next 5-minute redispatch market. Moving from the market k to the market k+1, the clearing price increases from $P_D(k)$ to $P_D(k+1)$ so that the dispatched load changes by $\dot{Q}_d(k) = Q_d(k+1) - Q_d(k) = (1-\alpha)\Delta Q_s(k)$ and the dispatched generation changes by $\dot{Q}_s(k) = Q_s(k+1) - Q_s(k) = -\alpha\Delta Q_s(k)$ where $0 \le \alpha \le 1$ to satisfy the physical constraint that $\dot{Q}_s(k) - \dot{Q}_d(k) = -\Delta Q_s(k)$ or $Q_d(k+1) = Q_d(k) = e_s$.

To respond efficiently to a frequency deviation, generation units must change their output by $\dot{Q}_s(k)$ as their contribution to restoring the area's export power to the committed hourly-scheduled level, as shown in Figure 5.4. Concurrently load must change demand by $\dot{Q}_d(k)$ as its contribution to efficiently restoring system frequency. The export power error at the time t is $\Delta Q(t) = Q(t) - Q_d(kt_d) = \Delta Q_s(kt_d) + Q_s(t) - Q_d(t)$. The economically optimal response is that for which the marginal cost of the generation response is equal to the marginal cost of the demand response. We compute the regulation response price, P(t) to quantify the marginal cost of deviations from the hourly schedule in real time:

$$P(t) = P_D(kt_d) + \frac{s(kt_d) \ d(kt_d)}{d(kt_d) - s(kt_d)} \Delta Q(t).$$

often cited as a potential solution, and (2) it provides a clearer illustration of the various effects on transactive system behavior.



Figure 5.4: Real-time response of generation and load to a disturbance.

where $s(kt_d)$ and $d(kt_d)$ are the slopes of the generation supply and load demand curves at the time of dispatch kt_d , respectively, for the redispatch exports $Q_d(kt_d)$ for the next 5 minutes, and Q(t) is the actual exports at the time t. In the 5-minute dispatch market k, $Q_d(k)$, s(k) > 0 and d(k) < 0 are updated every 5-minutes.

At the system level a deviation in net power will be associated with a deviation in frequency as well, regardless of whether the power deviation is endogenous to the local control area. For this reason we incorporate two additional cost components, one for the frequency deviation itself and the other for the control response arising from the ACE signal. The net cost taken over the entire system is zero in the sense that the payments made to areas mitigating a deviation are equal to payments by the areas contributing to it.

The total balance of payments is

$$\int_{0}^{300} P_D[\Delta Q(t) + B\Delta f(t)] - P(t)[A(t) - \Delta Q_s(t)]dt,$$
(5.2)

where P(t) is the cost of the over/under-response to the ACE signal A(t) as a result of the disturbance $\Delta Q_s(t)$. The value of P(t) will depend on the mix of generation (e.g., hydro, coal, nuclear, combine cycle gas turbine) that responds to the ACE signal. Any non-zero payments by any party represents a deviation from the surplusmaximizing condition represented by the schedule and therefore represents a loss of



Figure 5.5: Standard system for \mathcal{H}_2 -optimal control synthesis

surplus. Our objective then is to minimize these payments by expressing them as a weighted squared sum of the three cost components, Bf, p, and $P(t)(a - \Delta Q_s)/P_D$. This 2-norm minimization in the wake of a generation contingency of magnitude ΔQ_s is expressed by the objective

$$\min_{A(t)} \int_0^{300} \omega_1 [\Delta f(t)]^2 + \omega_2 \Delta_e^2(t) + \omega_3 \left(A(t) - \Delta Q_s(t) \right)^2 dt.$$
(5.3)

where $\omega_1 = B$, $\omega_2 = 1$ and $\omega_3 = \frac{P(t)}{P_D}$.

When this objective is satisfied, we can be assured that we have also maximized the total surplus given the prevailing conditions: by minimizing the individual payments or receipts on both sides of the balance of payments we have minimized the deviation from the surplus-maximizing schedule and therefore minimized the surplus loss due to regulation.

5.1.4 \mathcal{H}_2 -optimal control policy

We now have the conditions necessary to synthesize the \mathcal{H}_2 -optimal control policy for a control area that minimizes the costs associated with operating the system as it returns to the scheduled set-point, including frequency regulation in the presence of FADR resources. We require the individual component models within the control area used to synthesize the optimal control policy.

We now introduce the state-space solution of the \mathcal{H}_2 -optimal control problem [92]. We consider the standard control system in Figure 5.5 and we partition of the plant G according to

$$\begin{bmatrix} z \\ y \end{bmatrix} = \begin{bmatrix} G_{11} & G_{12} \\ G_{21} & G_{22} \end{bmatrix} \begin{bmatrix} v \\ u \end{bmatrix}.$$

The closed-loop system has the transfer function

$$z = F(G, K)v$$

where $F(G, K) = G_{11} + G_{12}(I - KG_{22})^{-1} + KG_{21}$. The \mathcal{H}_2 -optimal control problem consists of finding the causal controller K that stabilizes the plant G while minimizing the cost function

$$J_2(K) = ||F(G, K)||_2^2$$

where $||F(G, K)||_2$ is the \mathcal{H}_2 norm of the transfer function from v to z.

To obtain this transfer function we begin with non-dispatchable generation, primarily wind and solar resources. These resources do not contribute to either droop or ACE-control responses and have null responses to both frequency and ACE signal. The fraction of non-dispatchable generation in the study area is denoted F_w and for the design case we will use 75% renewable resource penetration to exemplify an extreme situation.

The thermal generating unit response to the filtered area generation control signal a_s is given by the simplified transfer function [90]

$$G_r(s) = \frac{\hat{g}_r(s)}{\hat{a}_s(s)} = \frac{1}{(1+sT_g)(1+sT_{ch})},$$
(5.4a)

where \hat{g}_r is the thermal unit's output, T_g is the governor time constant and T_{ch} is the time constant of the steam chest. Typical values for steam turbine units are [90]

$$T_{ch} = 0.3 \text{ sec}$$
 and $T_q = 0.2 \text{ sec},$

which gives the ACE-controlled generation response transfer function

$$G_r(s) = \frac{16.7}{(s+5.00)(s+3.33)}.$$
(5.4b)

The fraction of units that respond to the area generation control signal is denoted F_r which is set to 25% for the design case. All dispatchable units that do not respond to the area control error are provided with droop response such that [90]

$$G_d(s) = \frac{\hat{g}_d(s)}{\hat{f}(s)} = \frac{1}{R} G_r(s),$$
(5.4c)

where \hat{g}_d is the droop-controlled unit's output and R = -0.05 is the conventional frequency droop response of generating units. Given that we have selected a design case with the extreme of 75% renewable generation, we expect the number of droop units to be zero and this component is omitted from the design case model.

The filtered area generation control signal a_s is computed by sending the raw ACE signal through a low pass filter F to avoid excessive actuation of the regulating units. For the purposes of this study the values

$$B = 21$$
 and $F(s) = \frac{1}{1 + sT_f}$, (5.4d)

are used with $T_f = 0.02$ seconds.

Based on data obtained from field tests [48], the conventional grid-friendly control response exhibits two important behaviors. The first behavior is the primary underfrequency event response, which acts like a strong derivative response reaching maximum within a few seconds followed by a very slow recovery using integral error feedback over a period of a minute or more. These are approximated satisfactorily using the demand response transfer function

$$L(s) = \frac{\hat{l}(s)}{\hat{f}(s)} = \frac{F_d K_d s + K_p}{T_l s^2 + s + K_l},$$
(5.4e)

where l is the load response, F_d is the fraction of total load that is responsive, and for the design condition $K_d = 1/F_d$ is the fraction of responsive load that is armed by the 5-minute redispatch², and K_p is the quasi-steady state rebound response. The derivative response time constant $T_l = 0.17$ seconds and the recovery time constant $K_l = 0.01$ per second are based on the responses observed in the grid-friendly controllers studied in the Olympic test [48]. This gives us

$$L(s) = \frac{59s}{(s+5.8)(s+0.1)},$$
(5.4f)

as the general fast-acting demand response transfer function. The response of the loads is initially very fast and very strong, but it decays within a few minutes, and it is therefore minimally described as a second-order response with derivative control. The rebound response K_p is excluded in this model because it is expected to be

²Note $K_D F_D$ is unity at 5% DR but when F_D is changed K_D is not changed.

addressed by the redispatch operation after a maximum of 5 minutes. The load response is therefore not net-energy neutral over the 5-minute period. This allows us to suppress the non-minimum phase behavior that can emerge from thermostatic loads when their curtailment signal is released and they settle into a higher load condition for a prolonged demand response rebound period. For the controller design condition we use 5% controllable load resources, but the total demand response availability is varied from 0% to 50% for the control robustness analysis below.

The interconnected system's overall response to net power deviations is given by the damped inertial response transfer function

$$H(s) = \frac{\hat{f}(s)}{\hat{Q}(s)} = \frac{1}{Ms + D},$$
(5.4g)

where \hat{Q} is the response of all system generator output power, D = 1 is a typical value for the load damping constant, and M = 6 is a typical value for the system with somewhat low inertia [90].

Figure 5.6 illustrates the system. Each control area is modeled with: (1) loads L controlled by frequency through the controller K_L/R ; (2) frequency droop generators G_d controlled by the droop gain K_G/R , and (3) ACE-controlled generators using the controller K which we will design. The ACE input to the controller K considers the frequency droop -1/R, system damping D, and the export error $E_A - E_S$, while the frequency is obtained from the system inertial response 1/(Ms + D). The frequency input to ACE is defined as the bias B = D - 1/R.

The interconnected system's open-loop frequency, generation and load responses to a nearly step disturbance are shown in Figure 5.7. For the design condition we have set the demand response control gain to match the generation control gain as expected from the 5-minute market dispatch of the regulation contribution factors.

5.2 Implementation

We can now consider the \mathcal{H}_2 -optimal control design problem [93] for the system shown in Figure 5.6 and arranged in the standard form shown in Figure 5.8. The controller K provides coordinated dispatch of regulation response for generation resources G_r . The controller measures the system frequency f and the control area's net export schedule power deviation p. The current ACE control policy from Eq. (5.1) is the



Figure 5.6: System frequency and control area export regulation control diagram.



Figure 5.7: Model component frequency (f p.u. nominal frequency), load (l p.u. area load) and generation (g p.u. system load) responses to a local disturbance (ΔQ_s p.u. system load).

baseline control policy for this study. The frequency bias B is computed based on the generation and load characteristics of the control area [90].

A 5% generation local loss input disturbance is modeled as very nearly a step-loss

of generation in the local control area. The input filter for the power disturbance is thus specified as

$$\hat{\Delta}Q_s(s) = \frac{20\Delta Q_s}{s^2 + 20s + 0.01},$$
(5.5a)

where ΔQ_s is the magnitude of the disturbance, which for this study is set at 5% of the total system load. This magnitude disturbance corresponds to a deviation of $\Delta f = \lim_{x \to \infty} \frac{-d}{D} (1 - e^{-\frac{D}{M}t}) \times f = 3.0$ Hz, which is very significant for a 60 Hz system. This may seem like a large disturbance for a North American system. But it is not atypical for systems in other parts of the world or for microgrids. Demonstrating the effectiveness of transactive control in such systems in useful and therefore a large disturbance is considered. The remaining disturbances are taken as frequency and power measurement noise of magnitude of 1%.

The optimization seeks to minimize regulation deviations from the economically optimal schedule given by the most recent 5-minute dispatch of frequency responsive generation and load resources. Because the maximum surplus is achieved when the dispatch schedule is followed, any deviation from the schedule will reduce the total surplus. We therefore construct the \mathcal{H}_2 control output vector components

$$z(t) = \begin{bmatrix} C_A(t) \\ C_Q(t) \\ C_f(t) \end{bmatrix} = \begin{bmatrix} \frac{P(t)}{P_D} [A(t) - \Delta Q_s(t)] \\ C Q(t) \\ B f(t) \end{bmatrix},$$
(5.5b)

the 2-norm of which we will seek to minimize. The transfer function for the energy cost impact is given as nearly an integrator in the sense that it costs slightly more to provide an early generation response than a late one. The energy cost transfer function is approximated as

$$\hat{c} = \frac{1}{s^2 + 20s + 0.01}.$$
(5.5c)

The value P(t) is given in units of MW and B is given in units of MW/Hz.

The measurement outputs for power and frequency $y(t) = \begin{bmatrix} p(t) \\ f(t) \end{bmatrix}$ are taken directly from the system and the generation+load+disturbance outputs, respectively to which the input disturbance noises are added.

The control input for the raw area control signal is $u(t) = \lfloor A(t) \rfloor$ and will either be the ACE control signal

$$\hat{a} = \frac{1}{s}\hat{Q} + B\hat{f} \tag{5.5d}$$



Figure 5.8: Control area model in standard form.

for the baseline model, or the \mathcal{H}_2 -optimal controller output as described below for the study model.

5.2.1 State-space realization

Using the packed matrix notation $G = \begin{bmatrix} \mathbf{A} & | & \mathbf{B} \\ \hline \mathbf{C} & | & \mathbf{D} \end{bmatrix} = \mathbf{D} + \mathbf{C}(s\mathbf{I} - \mathbf{A})^{-1}\mathbf{B}$ we obtain the state-space realization for the study model of the control area given by Eq. (5.6a).

1	-0.1667	0	1.0417	-1.4706	0	0	-1	0	0	0	0.005	0	0]
	0	-8.3333	-4.1667	0	0	0	0	0	0	0.1333	0	0	0
	0	4	0	0	0	0	0	0	0	0	0	0	0
	0.6667	0	0	-5.8824	-0.2353	0	0	0	0	0	0	0	0
	0	0	0	0.25	0	0	0	0	0	0	0	0	0
	0	0	0	0	0	-20	-0.08	0	0	0	4	0	0
	0	0	0	0	0	0.125	0	0	0	0	0	0	0
G =	0	0	8.3333	-11.7647	0	0	$^{-8}$	-20	-0.08	0	0	0	0
	0	0	0	0	0	0	0	0.125	0	0	0	0	0
	0	0	0	0	0	0	0	0	0	-0.0167	0	0	0.0625
	0	0	0	0	0	0	0	0	0	0	0	0	1
	0	0	0	0	0	0	0	0	2	0	0	0	0
	7	0	0	0	0	0	0	0	0	0	0	0	0
	0	0	2.0833	-2.9412	0	0	$^{-2}$	0	0	0	0.01	0	0
	0.3333	0	0	0	0	0	0	0	0	0	0	0.01	0
													(5.6a)

	-0.1667	0	0	0	0	0	0	0	0	0	0.5	0	1
	0	-8.3333	-4.1667	0	0	0	0	0	0	0.1333	0	0	
	0	4	0	-0	0	0	-0	0	0	0	-0	0	
	0.6667	0	-0	-5.8824	-0.2353	0	0	0	0	0	0	0	Ĺ
	0	0	-0	0.25	0	0	0	0	0	0	0	0	
K =	0	0	-547.427	772.839	0	-20	525.45	0	0	0	262.765	0	Ι,
	0	0	8.6287	-12.1817	0	0.125	-8.2836	0	0	0	-4.1418	0	
	0	0	5.4743	-7.7284	0	0	-5.2553	-20	-0.08	0	1.3723	0	
	0	0	-0.0863	0.1218	0	0	0.0828	0.125	0	0	0.0414	0	
	-0.024	-0.0082	-0.0166	0.0047	-0.0667	0.0091	1.4543	-0.0006	-0.1	-0.0496	0	0	
	-0.3843	-0.1308	-0.2652	0.0759	-1.0671	0.1453	23.2695	-0.01	-1.6002	-0.5265	0	0	
	-										(5.	.6b)	

which yields the synthesized \mathcal{H}_2 -optimal regulation policy for the control area

and the corresponding transfer function from power p to area control a

 $\frac{-58.472(s+20)^2(s+5.6947)(s+5)(s+3.3333)(s+0.3625)(s+0.016667)(s+0.0086675)(s+0.0023866)}{(s+24.142)(s+19.999)(s+5.8723)(s+5.2747)(s^2+7.2484s+13.55)(s+0.16667)(s+0.010017)(s+0.0015464)}.$ (5.6c)

The smallest eigenvalue of the closed-loop system GK is -0.0005 and there are conjugate poles at $-3.6242 \pm 0.6443i$. Unlike the ACE control policy, the \mathcal{H}_2 -optimal area control policy does not rely on a frequency input and only requires measurement of net exports from the control area. By way of comparison, the conventional ACE control state-space model is given by

$$K_A = \begin{bmatrix} 0 & 1 & 0 \\ \hline 1 & 0 & B \end{bmatrix},$$
 (5.7)

where B = D - 1/R = 21, which is used for the baseline model. The smallest eigenvalue of the closed-loop system GK_A is -0.0005 and it has a single pair of complex conjugate poles at $-0.0367 \pm 0.0343j$.

5.2.2 Model Validation

The model of ACE control is verified for varying amounts of demand response under the design conditions, as illustrated in Figure 5.9. The ACE response is adequate for the conditions given insofar as it restores both frequency and power within about 120 seconds of the initial event. The \mathcal{H}_2 -optimal control response fully restores both frequency and power deviations to zero but with significantly less overshoot. Although it does not occur in this particular study, we anticipate that any residual transient error that persists at the end of a 5-minute dispatch interval will be corrected after the next dispatch or scheduling operation.

The area control signal (a) for \mathcal{H}_2 -optimal control is initially faster in its response to the initial event but of lesser magnitude. The power and frequency responses,



Figure 5.9: ACE control (black) and \mathcal{H}_2 -optimal (blue) control performance for design conditions (5% FADR), showing the raw ACE signal (*a* p.u. area load), area generation output (*p* p.u. system load), and system frequency (*f* p.u. nominal frequency) response to a loss of generation within the control area.

(p and f, respectively) are very similar for the first 10 seconds following the event. However afterwards the power and frequency response to \mathcal{H}_2 -optimal control signal is reduced to minimize costly overshoot.

The steady-state power and frequency deviation for both control policies is zero and both achieve steady-state in approximately the same time. As a result, the area control signal reaches the same steady-state value for both control policies.

5.3 Control Performance

We recognize that demand response resource availability can vary widely from one area to another, from hour to hour, and from season to season. Thus we evaluate the performance of the \mathcal{H}_2 -optimal control policy relative to the conventional ACE control policy by comparing the response of each to widely varying demand response resource availability. The area generation control signal, net power exports and system frequency are compared for a 100 MW load base control area with a nominal energy



Figure 5.10: ACE control (left) and \mathcal{H}_2 -optimal control (right) model validation for varying demand response level with generation response (g p.u. area load), demand response (l p.u. area load), and generation regulation cost (cg in \$/h p.u. area load).

price of \$100/MWh. In addition, the cost of regulation and energy used for regulation are compared.

The disturbance response of generation (p per unit area load) and load (l per unit area load) are shown in Figure 5.10 for the conventional ACE signal (left) and \mathcal{H}_2 -optimal control (right). In addition, the generation control cost c_g is shown in units of \$/h per unit area load. We observe decreasing stability of the ACE control policy under higher penetration of fast-acting demand response. This phenomenon is consistent with previously observed results for load controller delays that exceed 1/4 second [94]. In contrast, the \mathcal{H}_2 -optimal control policy exhibits less oscillation and shorter settling-time performance indicating that it is much less susceptible to overall performance degradation under high demand response scenarios. In every other important respect, and particularly with respect to the steady-state, the \mathcal{H}_2 optimal control policy is comparable to the ACE control policy.

The comparative costs contribution to the objective function are presented in Figure 5.11. The ACE control policy exhibits significantly more deviations from the schedule, particularly under high demand response conditions and is unable to establish a steady regulation regime under high demand response. In all conditions ranging from no demand response to 50% demand response, the \mathcal{H}_2 -optimal control policy establishing a steady regulation regime that zeros out the deviation of operation from the surplus maximized schedule within about 150-200 seconds.

The cost savings and energy impacts from utilizing \mathcal{H}_2 -optimal control are shown



Figure 5.11: ACE control (left) and \mathcal{H}_2 -optimal control (right) cost and dispatch for varying demand response levels, where C_a is the total control cost (in \$), C_Q is the power control response cost (in \$), and C_f is the frequency control response cost (in \$).

CONTROL		Cost			Generati	on	Exports			
FADR	ACE	\mathcal{H}_2	Saving	ACE	\mathcal{H}_2	Reduction	ACE	\mathcal{H}_2	Change	
(%)	(\$)	(\$)	(%)	(MWh)	(MWh)	(%)	(MWh)	(MWh)	(%)	
0	13750	13443	2.2	13.75	13.44	2.2	13.75	13.75	0.0	
1	13734	13389	2.5	13.73	13.39	2.5	13.75	13.79	-0.3	
2	13736	13382	2.6	13.74	13.38	2.6	13.75	13.79	-0.3	
5	13754	13427	2.4	13.75	13.43	2.4	13.75	13.77	-0.1	
10	13761	13469	2.1	13.76	13.47	2.1	13.75	13.74	0.1	
20	13822	13451	2.7	13.82	13.45	2.7	13.76	13.82	-0.4	
50	14264	13369	6.3	14.26	13.37	6.3	13.81	14.33	-3.7	

Table 5.1: Cost, generation, and net export impacts of ACE control versus \mathcal{H}_2 -optimal control

in Table 5.1. It is noteworthy that in all cases generation and energy costs are reduced, while exports are largely unchanged. We note that at very high FADR levels cost and generation are reduced more significantly while exports are impacted more clearly. This suggests that further study of the system behavior at very high levels of demand response may be desired in the future

5.4 Summary of Results

In this chapter we presented a \mathcal{H}_2 -optimal approach to synthesizing the control policy for control areas in bulk electricity interconnections. The approach is suited to controlling both generation and demand response in areas that have a high penetration of both intermittent renewable resources and fast-acting demand response. The implementation of the \mathcal{H}_2 -optimal control policy is compatible with, and indeed depends on the transactive control 5-minute dispatch strategy such as demonstrated by the Olympic and Columbus studies.

The transactive \mathcal{H}_2 -optimal area control policy is shown to be superior to the conventional ACE control policy in that it is (1) significantly more robust to uncertainty in the amount of fast-acting demand response that is available, (2) always less costly and less energy intensive, and (3) minimizes deviation from any surplus maximizing schedule.

Chapter 6

Dispatch

This chapter proposes a system-wide optimal resource dispatch strategy that enables a shift from primarily energy cost-based approach to primarily ramping cost-based one. This optimal dispatch answers the question of what power schedule to follow during each hour as a function of the marginal prices of energy, power and ramping over the hour¹. The main contributions of this chapter are (1) the derivation of the formal method to compute the optimal sub-hourly power trajectory for a system when the cost of energy and ramping are both of the same order, (2) the development of an optimal resource allocation strategy based on this optimal trajectory, and (3) a simulation method to evaluate the cost savings of choosing the optimal trajectory over the conventional sub-hourly dispatch used in today's system operation.

In Section 6.2 we develop the optimal control function in both time and frequency domains. In the case of the frequency domain optimal control function the solution is presented as a continuous function. A discrete-time solution suitable for periodic feedback control systems is presented in Section 6.3. In Section 6.4 we examine the performance of this optimal dispatch solution in terms of varying prices for a given "typical" hour, and in Section 6.5 we analyze the cost savings in an interconnection that models the Western Electric Coordinating Council (WECC) system for the year 2024 under both low (13%) and high (50%) renewable generation scenarios. A detailed discussion and synthesis of the consequences that appear to arise from this new paradigm and our perspective on possible future research on this topic are deferred Chapter 7.

¹The marginal price of a product or service is the change in its price when the quantity produced or delivered is increased by one unit.

6.1 Background

The conventional utility approach to addressing renewable generation variability is to allocate additional firm generation resources to replace all potentially non-firm renewables resources. This approach can have significant financial impacts in reducing the revenue from energy supply while increasing the costs of providing ramping response to variable generation. This chapter examines an approach to mitigating these financial impacts.

Firm resources are typically fast-responding thermal fossil resources or hydro resources when and where available. For new renewable resources the impact of this approach is quantified as an intermittency factor, which discounts the contribution of wind in addition to its capacity factor and limits the degree to which they can contribute to meeting peak demand [13]. However, the intermittency factor does not account for the ramping requirements created by potentially fast-changing renewable resources [14]. The need for fast-ramping resources discourages the dispatch of high-efficiency fossil and nuclear generation assets and can encourage reliance on low-efficiency fossil-fuel resources for regulation services and reserves [15].

One solution to overcoming the renewable generation variability at the bulk electric level is to tie together a number of electric control areas into a super-grid so that they can share generation and reserve units through optimal scheduling of system interties [1]. In an interconnected system, the combined power fluctuations are smaller than the sum of the variations in individual control areas. Furthermore, fast-acting energy storage systems and demand response programs can provide required ancillary services such as real-time power balancing [95] and frequency regulation [96] if they are equipped with suitable control mechanisms. A competitive market framework in which energy resources participate to sell and buy ancillary service products can accelerate the transition to a high-renewable scenario by supporting the long-term economic sustainability of flexible resources.

Concerns about the financial sustainability of utilities under high level of renewables are also beginning to arise. The question is particularly challenging when one seeks solutions that explicitly maximize social welfare rather than simply minimizing production cost [97]. The growth of low-marginal cost renewable resources can lead one to expect utility revenues to decline to the point where they can no longer recover their long term costs. But this conclusion may be erroneous if one fails to consider both the impact of demand own-price elasticity, as well as the impact of load control automation on substitution elasticity. The latter type of demand response can significantly increase the total ramping resource on peak and decrease ramping resource scarcity. One option for replacing energy resource scarcity rent is increasing fixed payments. But this may lead to economic inefficiencies as well as an unraveling of the market-based mechanisms built so far. Another option is to enable payments based on ramping resource scarcity rent through existing markets for ancillary services. At the present time, the majority of resources continue to be dispatched based on the energy marginal cost merit order. But it is not unreasonable to consider how one might operate a system in which the marginal cost of energy is near zero and resources are dispatched instead according the ramping cost merit order.

In the presence of high levels of variable generation, the scheduling problem is a co-optimization for allocating energy and ramping resources [98]. Under existing energy deregulation policies, there is usually a market in which energy producers compete to sell energy, and a separate market in which they compete to sell power ramping resources for flexibility. Producers get paid for their energy deliveries in the energy market and for power ramping flexibility in the flexibility market. But today's dual-pricing mechanism is dominated by the energy markets, which drives generation resources to secure revenue primarily in the energy market, and only deliver residual ramping resources in the flexibility market. Meanwhile poor access to energy markets leads loads and storage to seek participation primarily in the flexibility market while only revealing their elasticities to the energy market. This relegates loads and storage to only a marginal role in the overall operation of the system, which is the motivation for seeking policy solutions to improving their access to wholesale energy markets, such as FERC Orders 745 and 755.

6.2 Methodology

Consider a utility's cost minimization problem over a time interval T. The utility's customers purchase their net energy use E(T) at a pre-determined retail price. So in today's systems, profit maximization and cost minimization are essentially the same problem. For each hour the utility pays for energy delivered at a real-time location-dependent wholesale price that is also dependent on demand under typical deregulated nodal pricing markets. The utility's scheduled energy use is forecast for each hour based on its customers' expected net energy use, which is then used to compute the utility's net load over that hour. We assume that over any interval T


Figure 6.1: Power (left) and ramp (center and right) price functions.

the utility may incur additional costs for any deviation in actual net load from the scheduled load.

The price function at the operating point is split up into the marginal price of energy $a = \frac{\partial P}{\partial Q}$ (measured in $MW^2\cdot h$), the marginal price of power $b = \frac{\partial R}{\partial Q}$ (measured in MW^2), and the marginal price of ramping $c = \frac{\partial R}{\partial Q}$ (measured in $\dot{H}W^2$). In order to reflect resource scarcity all cost functions are assumed to be quadratic so that the price function for each is linear as shown in Figure 6.1. The marginal prices a and b determine prices as a function of the power demand Q, and the marginal price c determines prices based on the ramp rates \dot{Q} . The cost parameters arise from the schedule and may vary from hour to hour, but do not change within any given hour. Any of the marginal prices may be zero or positive depending on the market design and prevailing conditions in the system. For the purposes of this chapter, we will assume that they cannot be negative.

Over the time interval T the total cost of both the power trajectory Q(t) and the ramping trajectory $\dot{Q}(t)$ given the power price P(t) = aQ(t) and ramp price $R(t) = bQ(t) + c\dot{Q}(t)$, respectively, is given by

$$C(T) = \int_0^T P[Q(t)]Q(t) + R[Q(t), \dot{Q}(t)]\dot{Q}(t)dt.$$
(6.1)

Given the dispatch from Q(0) to Q(T) and the scheduled energy use $E(T) = \int_0^T Q(t) dt$ we augment the cost function with the Lagrange multiplier λ so that we have

$$\int_0^T a(Q-Q_z)Q + b(Q-Q_z)|\dot{Q}| + c\dot{Q}^2 + \lambda Q \ dt$$
$$= \int_0^T G(t,Q,\dot{Q})dt,$$

where the $|\dot{Q}|$ represents the magnitude of the ramp rate \dot{Q} , and Q_Z is the amount

of must-take generation having zero or effectively zero marginal energy cost. Then the optimal dispatch trajectory Q(t) is the critical function obtained by solving the Euler-Lagrange equation

$$\frac{\partial G}{\partial Q} - \frac{d}{dt} \frac{\partial G}{\partial \dot{Q}} = 0$$

From this we form a second-order ordinary differential equation describing the critical load trajectory

$$\ddot{Q} - \frac{a}{c}Q = \frac{\mu}{2c}.$$

where $\mu = \lambda - aQ_Z$. Using the Laplace transform we find the critical system response in s-domain is

$$\hat{Q}(s) = \frac{Q_0 s^2 + \dot{Q}_0 s + \frac{\mu}{2c}}{s(s^2 - \omega^2)},\tag{6.2}$$

where $\omega^2 = \frac{a}{c}$. The general time-domain solution for the critical function over the interval $0 \le t < T$ is

$$Q(t) = \left(Q_0 + \frac{\mu}{2a}\right)\cosh\omega t + \frac{Q_0}{\omega}\sinh\omega t - \frac{\mu}{2a},\tag{6.3}$$

•

where Q_0 and \dot{Q}_0 are initial power and ramp values.

We can determine whether this solution is an extremum by computing the second variation

$$\begin{aligned} \frac{\partial^2 C}{\partial Q^2}(T) &= \int_0^T [\alpha(v)^2 + 2\beta(vv') + \gamma(v')^2] dt \\ &= \int_0^T H(t) dt, \end{aligned}$$

with H(t) > 0 for all $v \neq 0$ subject to v(0) = 0 = v(T). We then have

$$\alpha = \frac{\partial^2 G}{\partial Q^2} = 2a, \quad \beta = \frac{\partial^2 G}{\partial Q \partial \dot{Q}} = b, \quad \gamma = \frac{\partial^2 G}{\partial \dot{Q}^2} = 2c.$$

Thus for all a, b, c > 0, H(t) > 0 and Q(t) is a minimizer. Since the only physical meaningful non-zero values of a and c are positive, this is satisfactory. We will examine

cases when a and c are zero separately. Note that when $\dot{Q} < 0$, we have b < 0, so that the sign of b does not affect the general solution.

Given the constraints $\int_0^T Q(t)dt = E_T$ and $Q(T) = Q_T$, which come from the hour-ahead schedule, we obtain the solution for μ and \dot{Q}_0 for the case where a, c > 0:

$$\begin{bmatrix} \mu \\ \dot{Q}_0 \end{bmatrix} = \begin{bmatrix} A & B \\ C & D \end{bmatrix}^{-1} \begin{bmatrix} E_\Delta \\ Q_\Delta \end{bmatrix}, \tag{6.4}$$

where

$$A = \frac{\sinh \omega T - \omega T}{2a\omega} \qquad B = \frac{\cosh \omega T - 1}{\omega^2}$$
$$C = \frac{\cosh \omega T - 1}{2a} \qquad D = \frac{\sinh \omega T}{\omega}$$
$$E_{\Delta} = E_T - \frac{\sinh \omega T}{\omega} Q_0 \qquad Q_{\Delta} = Q_T - Q_0 \cosh \omega T.$$

When a = 0, the cost of energy is zero and only the ramping cost is considered. Then the time-domain solution is

$$Q(t) = \frac{\mu}{4c}t^2 + \dot{Q}_0t + Q_0, \tag{6.5}$$

with

$$A = \frac{T^3}{12c} \qquad B = \frac{T^2}{2}$$
$$C = \frac{T^2}{4c} \qquad D = T$$
$$E_{\Delta} = E_T - Q_0 T \qquad Q_{\Delta} = Q_T - Q_0,$$

which gives the critical response in s-domain

$$\hat{Q}(s) = \frac{\mu}{4cs^3} + \frac{\dot{Q}_0}{s^2} + \frac{Q_0}{s}.$$

When c = 0, there is no scarcity for ramping so that the ramping price is based only on the marginal energy cost of additional units that are dispatched. Then we have the time-domain solution

$$Q(t) = -\frac{\mu}{2a},\tag{6.6}$$



Figure 6.2: Optimal dispatch controller diagram with discrete update time t_s .

with

$$\mu = -\frac{2aE_T}{T}.$$

This gives the critical response is s-domain

$$\hat{Q}(s) = -\frac{\mu}{2as},$$

and the initial and final ramps from Q(0) to $-\frac{\mu}{2a}$ and from $-\frac{\mu}{2a}$ to Q(T) are limited by the ramping limits of the responding units.

6.3 Optimal Dispatch Controller

The partial fraction expansion of Eq. 6.2 is

$$\frac{K_1}{s+\omega} + \frac{K_2}{s} + \frac{K_3}{s-\omega},\tag{6.7}$$

where $K_1 = \frac{Q_0}{2} - \frac{\dot{Q}_0}{2\omega} + \frac{\mu}{4a}$, $K_2 = -\frac{\mu}{2a}$, and $K_3 = \frac{Q_0}{2} + \frac{\dot{Q}_0}{2\omega} + \frac{\mu}{4a}$, with the values of the parameters are computed from Eq. 6.4.

The initial response of the optimal controller is dominated by the forward-time solution

$$K_1 \ e^{-\omega t} = \mathcal{L}^{-1} \left[\frac{\frac{Q_0}{2} - \frac{\dot{Q}_0}{2\omega} + \frac{\mu}{4a}}{s + \omega} \right] (s),$$

which handles the transition from the initial system load Q_0 to the scheduled load

 $Q_E = -\frac{\mu}{2as}$. The central response is dominated by the scheduled load solution

$$K_2 = \mathcal{L}^{-1} \left[-\frac{\mu}{2as} \right] (s)$$

Finally, the terminal response is dominated by the reverse-time solution

$$K_3 e^{\omega t} = \mathcal{L}^{-1} \left[\frac{\frac{Q_0}{2} + \frac{\dot{Q}_0}{2\omega} + \frac{\mu}{4a}}{s - \omega} \right] (s),$$

which handles the transition from the scheduled load to the terminal load Q_T . A discrete-time controller that implements the solution of Eq. 6.7 is shown in Figure 6.2. The controller implements the three main components to the optimal solution with step inputs μ , Q_0 , and \dot{Q}_0 . Note that the marginal prices a, b and c for the entire hour are constants in the controller blocks, which makes the controller design linear time-invariant within each hour, but time-variant over multiple hours. The discrete-time solution is then

$$Q^*(k) = \begin{cases} K_1 \tau^k + K_2 + K_3 \tau^{-k} & : a > 0, c > 0\\ \frac{\mu}{4c} t_s^2 k^2 + \dot{Q}_0 t_s k + Q_0 & : a = 0, c > 0\\ -\frac{\mu}{2a} & : a > 0, c = 0 \end{cases}$$

where $\tau = e^{\omega t_s}$.

The discrete-time dispatch control is illustrated in Figure 6.3 for various values of $\omega = \sqrt{a/c}$. When the value of ω is large, the optimal dispatch is dominated by the energy cost and the cost of high ramp rates is negligible compared to the energy cost. The result is a dispatch that moves as quickly as possible to scheduled load Q_E . In the limit of zero ramping cost, the optimal response is a step function². As the cost of ramping increases relative to the energy cost, the optimal dispatch begins to reduce the ramp rate while still following a trajectory that satisfies the hourly energy delivery requirement. In the limit of zero energy cost, the optimal dispatch trajectory is parabolic.

 $^{^{2}}$ Step responses are only possible by generation or load tripping, which is not considered as part of the conventional control strategy.



Figure 6.3: Optimal discrete time control for various values of ω at $t_s = 5$ minutes.

6.4 Performance Evaluation

In this section we develop the cost performance metric of the optimal dispatch control design. The optimal dispatch cost function is found by evaluating Equation 6.1 using

Equations 6.3, 6.5 and 6.6. Thus when a, b, c > 0 we have³

$$C(T) = \frac{\sinh 2\omega T}{2\omega} \left[a(A^2 + B^2) + bAB\omega \right] + \frac{\sinh^2 \omega T}{2\omega} \left[b(A^2 + B^2)\omega + 4aAB \right] + \frac{\cosh \omega T - 1}{\omega} \left[(bA\omega + 2aB)C - (aB + bA\omega)Q_z \right] + \frac{\sinh \omega T}{\omega} \left[(bB\omega + 2aA)C - (aA + bB\omega)Q_z \right] + \left[aC^2 - aCQ_z \right] T.$$

where $A = Q_0 + \mu/2a$, $B = \dot{Q}_0/\omega$ and $C = -\mu/2a$. For the case when a = 0 we have

$$C(T) = \frac{b\mu^2}{32c^2}T^4 + \frac{3b\mu\dot{Q}_0 + \mu^2}{12c}T^3 + \left(\frac{b\dot{Q}_0^2}{2} + \frac{b\mu(Q_0 - Q_z)}{4c} + \frac{\mu\dot{Q}_0}{8c^2}\right)T^2 + \left(b\dot{Q}_0(Q_0 - Q_z) + c\dot{Q}_0^2\right)T^2$$

When c = 0 we have

$$C(T) = aE_T\left(\frac{E_T}{T} - Q_z\right).$$

We use as the base case a conventional unit dispatch strategy that requires generators ramp to their new operating point during the 20 minutes spanning the top of the hour. Accordingly the generators begin ramping 10 minutes before the hour and end ramping 10 minutes after the hour. In the aggregate for a given hour this strategy is illustrated in Figure 6.4 where

$$Q_E = \frac{6}{5} \left(E_T - \frac{Q_0 + Q_T}{12} \right),$$

with the initial and terminal ramp rates

$$\dot{Q}_0 = 6(Q_E - Q_0)$$
 and $\dot{Q}_T = 6(Q_T - Q_E).$

Three cases are shown: overproduction to compensate for a lack of generation in previous hours (top), scheduled production (center), and underproduction to compensate for extra generation in previous hours (bottom).

³Note that if the ramp rate \dot{Q} changes sign at the time $t_c = \frac{1}{\omega} \tanh^{-1}(-\frac{B}{A})$ and $0 < t_c < T$, then we must divide the cost integral into two parts to account for the absolute value of \dot{Q} on b terms.



Figure 6.4: Conventional power dispatch for base case: (top) significant negative schedule error requiring over-production, (center) small negative, zero and positive schedule error requiring over (red), normal (black) and under (blue) production, and (bottom) significant positive schedule error requiring under-production.

The cost of the base case is then

$$C_{base}(T) = \frac{aT}{18}(Q_T^2 + Q_T Q_E + 14Q_E^2 + Q_E Q_0 + Q_0^2) - \frac{aT}{12}(Q_T + 10Q_E + Q_0)Q_z + |\frac{b}{2}(Q_E - Q_0)|(Q_E + Q_0 - 2Q_z) + |\frac{b}{2}(Q_T - Q_E)|(Q_T + Q_E - 2Q_z) + \frac{6c}{T}(Q_T^2 - 2Q_T Q_E + 2Q_E^2 - 2Q_0 Q_E + Q_0^2).$$

The zero-order hold ramp discrete form of Equation 6.1 gives us the cost of operating with a discrete control time-step t_s , i.e.,

$$C^{*}(T) = \sum_{k=0}^{T/t_{s}} \left(P^{*}[Q^{*}(k)]Q^{*}(k) + R^{*}[Q^{*}(k), \dot{Q}^{*}(k)]\dot{Q}^{*}(k) \right) t_{s}$$

$$= \sum_{k=0}^{T/t_{s}} \frac{at_{s}}{4} \left[Q^{*}(k)^{2} + 2Q^{*}(k)\dot{Q}^{*}(k) + \dot{Q}^{*}(k)^{2} - 2Q_{z}[Q^{*}(k) + \dot{Q}^{*}(k)] \right]$$

$$+ \frac{1}{2} \left[\left| b(\dot{Q}^{*}(k) - Q^{*}(k)) \right| (\dot{Q}^{*}(k) + Q^{*}(k) - 2Q_{z} \right]$$

$$+ \frac{c}{t_{s}} \left[Q^{*}(k)^{2} - 2Q^{*}(k)\dot{Q}^{*}(k) + \dot{Q}^{*}(k)^{2} \right]$$

where $Q^*(k) = Q(kt_s)$ and $\dot{Q}^*(k) = Q^*(k+1)$. We evaluate the performance of the control strategy for different control update rates t_s using two future scenarios, one for low renewables where $\omega > 1$, and one for high renewables where $\omega < 1$ for both unconstrained and constrained transmission operating conditions.

6.5 Case Study: WECC 2024

In this section we examine the cost savings associated with using the optimal control solution on the WECC 2024 base case model introduced in [1]. The WECC 2024 model is a 20-area base case used by WECC for planning studies. The 20-area model combines a number of smaller control areas based on the anticipated intertie transfer limits reported in the WECC 2024 common case [99]. In this model constraints within control areas are ignored, while internal losses are approximated. The peak load, annual energy production and demand consumption are forecast, including intermittent wind, solar, and run-of-river hydro for the entire year. The demand characteristics, generation capacity, production costs and tieline limits are given in Tables C.2 through C.6.

The model also includes a hypothetical market for each consolidated control area, with a flat zero-cost supply curve for all renewable and must-take generation resources and a constant positive supply curve slope for all dispatchable units. The hourly generation of intermittent resources is provided by the base case model and incorporated into the supply curve so that there is effectively no marginal cost of production for renewable energy and must take generation. All generating units are paid the hourly clearing price, and when the marginal energy price in a control area is zero then renewable generation may be curtailed. As a result, under the high renewable scenario, zero energy prices are commonplace and renewable generation is curtailed more frequently. Demand response is similarly considered for each control area and the output of this scheduling model provides the hourly nodal prices required to satisfy the transmission constraints, if any.

The low renewables case is the WECC forecast for the year 2024, which correspond to 29.5 GW (16.1%) of renewable capacity and 140.8 TWh (13.4%) of annual renewable generation. The high renewables case is given as 400% of capacity of the WECC forecast for the year 2024, which corresponds to 117.8 GW (63.5%) and 523.9 TWh (49.6%) respectively. The blended energy price of operations is \$130.6/MWh and \$50.2/MWh for the low and high renewables cases, respectively.

The ramping price was not considered in the WECC 2024 base case model. For this study we have assumed that the ramping energy cost is based on the marginal energy cost for the dispatchable generation and the demand response, as well as the cost of changing the dispatchable generation output, as shown in Table 6.1. In both cases, the marginal price of power b is the average marginal price of energy a over the hour. In the low renewables case the marginal price of ramping c is the marginal price of power b multiplied by 12 seconds. In the high renewables case, c is the marginal price of power b multiplied by 49 hours. The value of ω is approximately 121 times greater in the low renewable case than it is in the high renewable case. Note that a is zero when renewables are curtailed while b is assumed to also be zero because curtailed renewables and demand response are presumed to be dispatchable.

The values of the ramping response constant c were also selected such that the overall cost of operating the system remains more or less constant when going from the low to high renewables scenarios under the base case. This allows us to evaluate the impact of the optimal control strategy without involving the question of revenue adequacy under the high renewables scenario. Given that there are few markets from which to determine these values, we must be satisfied with this assumption for now.

The statistical nature of the intermittency and load forecast errors and their connection to load following and regulation was studied at length in [100]. The authors showed that consolidated control of WECC could yield both cost savings and performance improvements. In particular, the study showed that with high accuracy control 1% standard deviation in load forecast was expected, with 0% real-time mean



Figure 6.5: Single hour optimal dispatch for low (top) and high (bottom) renewables with a ramp from 100 GW to 110 GW using a 10-minute discrete-time dispatch control rate, with hourly energy schedule correction errors varying from -5% to +5%.

error at 0.15% standard deviation at peak load. However, for the purposes of a preliminary study like the one presented in this chapter, we will consider the scheduling error to be Gaussian with a mean error of 0 MW and a standard deviation of 100 MW. We believe that energy and flexibility markets should be efficient enough to remove all systematic error from the price signals leaving only the random noise that is satisfactorily modeled by Gaussian noise.

The comparison of the conventional and optimal dispatch for a typical case is shown in Figure 6.5. The conventional control strategy is shown in dotted lines, with the 10 minute optimal-dispatch trajectory shown as solid lines. Note that the ramp rate is constant between discrete control updates. The evaluation is completed with the marginal prices and marginal costs at 100 GW, as shown in Table 6.1. The energy schedule changes according to a varying energy error remaining at the end of the previous dispatch interval. A -5% error represents an energy deficit of 5 GWh for a 105 GWh schedule, while a +5% error represents an energy surplus of 5 GWh.

The marginal prices in Table 6.1 are chosen to satisfy the following conditions:

Variable	Base case	Study case	Units			
Marginal prices:						
a	1.27×10^{-3}	6.34×10^{-4}	$MW^2 \cdot h$			
b	1.27×10^{-3}	6.34×10^{-4}	MW^2			
c	4.23×10^{-6}	3.09×10^{-2}	$\cdot h/MW^2$			
Marginal costs:						
P	133.09	66.55	\$/MW·h			
<i>R</i>	133.13	375.19	MW			
ω	17.3	0.1433	h^{-1}			

Table 6.1: Marginal prices and marginal costs for 105 GWh schedule at 100 GW initial power and 10 GW/h ramp for cases in Figure 6.5

Table 6.2: Single hour cost savings under low and high renewable for a ramp from 100 GW to 110 GW at 5 minute discrete dispatch control update rate, with varying energy error redispatch

Dispatch		Refere	nce Cos	t		Optin	nal Cost		Cos	t	Dispatch
Energy	Energy	Ramp	Total	Price	Energy	Ramp	Total	Price	Savin	gs	Error
(GWh)	(\$M)	(M)	(\$M)	(%)MWh	(\$M)	(\$M)	(\$M)	(%)MWh	(\$M/h)	(%)	(%)
Low renew	Low renewable scenario										
110.3	10.8	1.2	12.0	108.62	10.8	1.1	11.9	107.93	0.1	0.6	-0.8
107.1	10.1	0.9	11.0	102.50	10.1	0.9	11.0	102.50	0.0	0.0	-0.4
105.0	9.6	0.9	10.5	100.00	9.6	0.9	10.5	99.98	0.0	0.0	0.0
102.9	9.1	0.9	10.0	97.53	9.1	0.9	10.0	97.51	0.0	0.0	0.4
99.8	8.4	1.1	9.6	96.06	8.4	1.1	9.5	95.42	0.1	0.7	0.9
High renewable scenario											
110.3	1.6	24.1	25.7	232.77	1.6	13.5	15.1	136.75	10.6	41.3	-2.0
107.1	1.3	11.7	13.0	121.55	1.3	4.8	6.1	57.27	6.9	52.9	-0.8
105.0	1.1	9.4	10.5	100.00	1.1	3.2	4.3	41.25	6.2	58.8	-0.0
102.9	1.0	11.7	12.7	123.35	1.0	4.8	5.8	56.43	6.9	54.2	-0.7
99.8	0.7	24.1	24.8	248.95	0.8	13.4	14.2	142.37	10.6	42.8	-1.9

- 1. The system operating cost is roughly \$100/MWh at a system load of 100 GW.
- 2. For the low renewables case, the energy cost is roughly 10 times the ramping cost, while for the high renewables case the ramping cost is roughly 10 times the energy cost for the nominal schedule. This was necessary to ensure that costs were the same for both cases.
- 3. The marginal power price b for both cases is equal to the marginal energy price a of the respective case.

We considered the performance degradation resulting from longer dispatch in-

	Cost				
Scenario	Base case	Optimal	Savings		
Model	(\$B/y)	(B/y)	(\$B/y)		
Unconstrained:					
Low	126.0	125.9	0.16 (0.1%)		
High	108.6	77.8	30.85~(28.4%)		
Constrained:					
Low	184.4	184.1	0.26 (0.1%)		
High	388.3	231.2	157.12~(40.5%)		

Table 6.3: WECC 2024 cost savings from optimal dispatch under different transmission constraint and renewable scenarios

Table 6.4: Summary of energy and price impacts of optimal dispatch control for the WECC 2024 base case

Total	Price				
Energy	Base case	Optimal			
(TWh)	(% MWh)	(MWh)			
ined:					
1054.6	119.5	119.35 (-0.1%)			
1067.2	101.8	67.29 (-51.2%)			
Constrained:					
1054.5	174.8	174.55 (-0.2%)			
1055.7	367.8	87.96 (-318.2%)			
	Total Energy (TWh) <i>nined:</i> 1054.6 1067.2 <i>ed:</i> 1054.5 1055.7	Total Base case Energy Base case (TWh) (\$/MWh) nined: 1054.6 1067.2 101.8 ned: 1054.5 1054.5 174.8 1055.7 367.8			

tervals by evaluating the performance using 5-minute updates, 1 minute updates, and 4-second discrete control time steps but found no appreciable difference in the economic performance. The results shown in Table 6.2 are shown for the 5-minute dispatch interval. The output of the presented discrete control method is a load profile that does not necessarily lead to the scheduled hourly energy, because the load trajectory over each time interval (which is linear) is slightly different from the optimal load trajectory (that often has a curvature). One approach to deal with this energy deficiency is to use a higher time resolution, so that the trajectories lie on each other more precisely. Another approach is to adjust the targeted load such that it delivers the scheduled energy over each time interval. In this case, the discrete control load is not necessarily equal to the optimal load.

Generally, at low levels of renewables, savings are not possible using the optimal control strategy. The cost savings observed in the extreme low renewables dispatch



Figure 6.6: WECC 2024 load duration (top) and optimal dispatch savings duration (bottom) using discrete optimal control at 5-minute dispatch rate for the unconstrained (left) and constrained (right) high renewables scenario. The scatter plots are the corresponding cost (top) and load (bottom) values for the durations curves shown.

cases in Table 6.2 are due to the fact that discrete dispatch control follows the optimal trajectory sampling every t_s seconds. This dispatch error can result in small over or underproduction depending on the degree of asymmetry in the optimal trajectory.

At higher levels of renewables the savings are potentially more significant. In addition, the savings are maximum when dispatch tracks the original schedule, which suggests that there may be a strong economic incentive to avoid carrying over energy tracking error from one schedule interval to the next.

The interconnetion-wide scheduling solution in [1] includes a 20-area constrained solution. The hourly energy prices for each area are computed considering both supply and demand energy price elasticities. The energy prices are computed for the interconnection-wide surplus-maximizing schedule over the entire year. The marginal power price is the price of energy for the schedule hour. The marginal price of ramping is 1/300 marginal price of power in the low renewable case, and 49 times the marginal price of power in the high renewable case. The costs, savings and price impact of using this scheduling solution compared to the base case are presented in Tables 6.3 and 6.4. The unconstrained solution is evidently less costly because the combined system-wide fluctuations are smaller than the sum of the individual variations in each balancing authority.

The WECC 2024 system-wide load and savings duration curves⁴ are shown in Figure 6.6. The potential savings are very significant for all scenarios, with the highest savings being found when high levels of renewable resources are available. The savings when more transmission constraints are active are augmented considerably with respect to unconstrained system conditions.

6.6 Summary of Results

The principal result of this chapter is that the use of an optimal dispatch strategy that considers both the cost of energy and the cost of ramping simultaneously leads to significant cost savings in systems with high levels of renewable generation. For the WECC 2024 common case the savings can exceed 25% of total operating costs in the high renewables scenario.

As the bulk power interconnection resource mix shifts from primarily dispatchable non-zero marginal fuel cost resources (e.g., natural gas) to primarily non-dispatchable renewable resources (e.g., hydro, wind, solar) we expect a steady shift in bulk system revenue from energy scarcity rent to ramping scarcity rent. While the total revenue must remain largely the same for financial sustainability, the scarcity pricing mechanism must change.

⁴A duration curve shows the number of hours per year that a time-series quantity is above a particular value. It is obtained by sorting the time-series data in descending order of magnitude and plotting the resulting monotonically descending curve.

Chapter 7

Discussion

In this chapter we synthesize and discuss more generally the significant results, observations, and outstanding issues arising from the development of a hierarchical inter-temporal solution to transactive control at the interconnection scale.

Transactive control, and more broadly transactive energy require coordination of economic, technical and consumer processes at every scale, both physical and temporal as shown in Figure 7.1. In a conventional power system, scheduling, dispatch, and regulation are established using dissimilar mechanisms according to the prevailing physical or temporal scale. In contrast to this, transactive control systems seek to employ a common scale-free price-based coordination mechanism. This requires a certain degree of uniformity in the coordination approaches at each scale, which in turn requires us to demonstrate that we can model and control control systems that can work with prices over a wide range physical and temperal system scales. This thesis has demonstrated both observation (bidding) and control (response) strategies that support a transactive approaches for several important processes at different scales of grid operation, i.e., aggregate observation and control of periodic demand, control area of system frequency and inter-area power exchange, and optimal control area dispatch.

In this thesis we have examined four important areas of transactive control system design. These are aggregate demand response observation and control, frequency regulation and optimal dispatch. Each section in this chapter discusses these in more detail with Chapters 3, 4, 5, and 6 discussed in Sections 7.1, 7.2, 7.3, 7.4 respectively.



Interarea Transactions Control

Control Area Transactions





Figure 7.1: Physical (top) and temporal (bottom) system diagram of transactive control systems.

7.1 Demand Response

The availability of a more accurate model of aggregated demand response can be expected to support a wide range of new work on controllable load using real-time pricing. Long-term demand response behavior models do not support the design and analysis of fast-acting demand response as well as the proposed short-term model. In this section we discuss the advantages of using short-term demand response models. As an equilibrium model, the random utility model is expected to be valid for both small signal control stability analysis as well as certain tariff design problems.

7.1.1 Model Limitations

The random utility model is not necessarily valid in its current form for large price disturbance. Roozbehani et al. [82] examined the feedback stability question in the context of wholesale markets and found that real-time wholesale prices could create an unstable closed-loop feedback system for both ex-ante and ex-post settlement



Figure 7.2: Demand (left) and elasticity (right) curves for a nominal case with $\eta_D = -2.5$ and $\bar{P} = 0.5$.

systems. It was established that the absence of an inelastic component in demand contributed to instability, supporting the intuition that increasing feedback gain from price-responsive demand is a concern. Static demand elasticity was also found to lead to loss of efficiency. In follow-up work on price volatility, the authors found that although demand bidding mechanisms eliminate the exogenous feedback delays inherent in settlement-based systems, there remain endogenous load dynamics that can cause bidding mechanisms to exhibit instability [101] and consequently more sophisticated models of demand and consumer response to real-time price dynamics may be required.

The random utility model does not account for the aggregate equilibrium duty cycle of thermostatic loads. In its simplest form, the model assumes a 50% effective duty cycle. The duty cycle tends to skew the demand curve away from the more probable load $\hat{Q} = Q_U + \frac{1}{2}Q_R$. Incorporating this effect would most likely improve the model, particularly with respect to bias error and standard deviation.

When a significant price deviation occurs relative to the natural diversity state, the loads enter a transient response regime. If we compare maximum entropy from Eq. (3.5) to the minimum elasticity from Eq. (3.6) we find that they occur at different prices. Specifically, load state diversity is maximized when $P = \overline{P}$, but demand elasticity

$$\eta(P) = \frac{-bPe^{a+bP}}{1+e^{a+bP}}.$$

is minimized when

$$P = \bar{P} \frac{W(e^{2\eta_D - 1}) + 1}{2\eta_D}$$

where W is the Lambert W-function

$$W(z) = \sum_{n=1}^{\infty} \frac{(-n)^{n-1}}{n!} z^n.$$

For values of z approaching zero this function is well approximated by z, giving:

$$P \approx \bar{P} \frac{e^{2\eta_D - 1} + 1}{2\eta_D}$$

The price at which elasticity is minimized is always greater than \bar{P} for all $0 < Q < Q_R$ when $Q_U > 0$. (Note that Q_U is typically positive, except when a high surplus of uncontrollable distributed generation is present, such as might occur with significant deployment of rooftop solar photovoltaics.) This implies that in equilibrium demand elasticity will tend to increase with prices, as illustrated in Figure 7.2. Under such conditions thermostatic devices no longer follow the equilibrium duty cycle regime and their states diverge from the equilibrium distribution. Consequently their bids depart from the logistic probabilities and no longer follow the bid price distribution of Equation (3.8).

In addition, if the price deviates too quickly, then a diabatic¹ response governs the change in state diversity. As diversity decreases the equilibrium price moves further from the most probable price and the elasticity of demand changes significantly. Decreasing elasticity is observed when loss of diversity favors loads that are on and the bid distribution skews left. The distribution skews to the right with increased elasticity when diversity favors loads that are off. Note that the periodic behavior of thermostatic loads means that diversity is expected to fluctuate in such a way that elasticity oscillates with damping of about a/2 arising from the diversity in the ther-

¹The term 'diabatic' here is used in analogy to non-adiabatic processes, i.e., a diabatic process is one in which a significant fraction of the macroscopic state arises from changes in the distribution or arrangement of microscopic states rather than only from the sum of individual states. In other words the total response include a significant contribution from changes system entropy.

mal properties of the home and frequency related to the population average cycling time of the heating/cooling systems.

Device state diversity appears to be a key characteristic that governs demand response. True state diversity can be measured by taking the weighted generalized mean M_{q-1} of the proportional occupancy of states in the population of responsive devices, and then taking the reciprocal of this quantity to obtain the density of devices in states. The diversity of order-q is then defined as

$$D_q \equiv \frac{1}{M_{q-1}} = \left(\sum_{n=1}^N p_n^q n\right)^{1-q^{-1}}.$$
 (7.1a)

In the limit of q = 1, the first-order mean occupancy is well-defined and its natural logarithm converges to

$$H = -\sum_{n=1}^{N} p_n \ln p_n \tag{7.1b}$$

This is simply the Shannon entropy calculated using natural logarithms instead of base-2 logarithms [102].

Given the linear relationship of bid price to the device state, we use the bid price entropy norm as a measure of state diversity, as shown in Table 7.1. A higher bid price entropy is associated with a higher state diversity. This further explains why the Olympic results fit the equilibrium state assumptions of the random utility model so much better than the Columbus results.

If the demand response resource is very limited it can be expected to saturate more often and lead to reduced diversity and reduced entropy. This effect is illustrated by the reduced diversity duration curves of the Columbus experiments shown in Figure 7.3. In such cases, we expect the full DR and no DR models to be as accurate as the random utility model when DR is called and released, respectively and the half DR model to be more accurate when DR is not called. This condition is more clearly evident in the Columbus data where the total resource was relatively small compared to the total feeder capacity. The observed fluctuations in unresponsive load result in large changes in demand response and lead to DR control saturation, thus making the alternative models satisfactory when compared to the random utility model.



Figure 7.3: Demand response state diversity duration curves for the Olympic feeder and Columbus feeder numbers 120, 140, 160, and 180.

Load State Entropy				
System	Mean	Standard Deviation		
Olympic	0.68	0.19		
Columbus 120	0.54	0.20		
Columbus 140	0.60	0.18		
Columbus 160	0.47	0.17		
Columbus 180	0.51	0.17		

Table 7.1: Bid price entropy statistics

7.1.2 Technical and Regulatory Impacts

Interest in transactive control has also resulted in renewed discussion of tariff design and rate-making processes for utilities that wish to adopt the real-time pricing strategy. The Columbus demonstration included a rate case for the real-time price double auction called "RTPda" that was approved by the Public Utility Commission of Ohio [103, 104]. However, real-time price tariffs and rate designs can be difficult to study when loads respond to hourly or sub-hourly prices. These tariffs present new challenges for utilities and regulators alike. Concerns have also been expressed regarding customer acceptance of real-time prices [58] but utilities could offer a portfolio of tariffs, including a real-time price, from which customers may choose. The rate at which tariffs are adopted then becomes a conventional portfolio optimization problem where opt-in/opt-out incentives and penalties are offered to achieve tariff adoption mixtures that meet utility and regulator objectives [105].

The implications of adopting the random utility demand response model for both utilities and regulations have yet to be explored fully. However, some initial thoughts may foster discussion and suggest further research on methods to effectively incentivize enduring and sustainable demand response from residential customers.

First, the existence of upper and lower price asymptotes is often overlooked in demand response analysis for electricity loads. We recognize that linearization of the demand function is often necessary. But the asymptotes require us to acknowledge the existence of hard upper and lower constraints on short-term responsive load. When prices deviate from the most probable price, the elasticity of demand approaches zero. Thus an important change occurs in fast-acting demand response when prices induce load to move into either curtailment or pre-heat/pre-cool/recovery regimes: load diversity is decreased and important endogenous load oscillations can be induced, which are independent of the oscillations induced by control feedback. Unless technical steps are taken to dampen endogenous load oscillations before they occur, price oscillations can emerge that can only be mitigated by reducing the feedback from load and waiting for load state diversity to be restored. It is therefore incumbent on utilities to identify all the conditions under which instability can emerge and implement either market and/or load control mechanisms to mitigate them.

Second, existing residential electricity tariffs do not adequately support the development of fast-acting demand response or the mechanisms needed to mitigate the potential instabilities associated with demand response. This is particularly a concern in the presence of supply resources at the distribution level, such as rooftop photovoltaic panels and significant amounts of battery storage, such as so-called vehicle-togrid discharging. Clearly the availability of such resources can be easily incorporated into the market mechanism demonstrated in both the Olympic and Columbus trials. However, the marginal cost of most renewable retail resources is effectively zero, which not only can give rise to revenue adequacy problems for utilities, but can also effectively shut off the very price signaling mechanism needed to control load. Strategic bidding may be necessary for these resources to elicit non-zero price signals, as was demonstrated in the Olympic study to manage minimum and maximum generation run time limits. However, strategic bidding at the retail level entails an entirely new class of regulatory problems that may require mitigation strategies that are not part of current tariff design and approval procedures.

Demand response in residential settings presents an additional challenge to utilities. Historically, the cost-per-point and cost-per-megawatt for the supporting infrastructure and management of these systems has been significantly higher than for commercial and industrial customers. Recent industry estimates suggest that customer-premises portals and in-home energy management systems will cost between \$US150 and \$US300 by 2030 [106]. But life-cycle cost analysis for transactive technology is not generally available yet, in part due to the lack of simulation tools that can properly evaluate the benefits of the technology [107]. Fast-acting demand response requires higher communication rates than hourly or day-ahead critical peak pricing mechanisms used for commercial and industrial demand management. Automated metering infrastructure has offered the promise of fast and accurate communications with residential loads. But much of that promise has yet to be analyzed in detail or realized in practice, either with incentive-based or even direct load control mechanisms.

The cost per unit of power reduced of behind-the-meter infrastructure for residential loads has been typically difficult to compare to the cost per energy saved using long-term demand response programs. The additional costs per customer tends to delay adoption of residential demand response programs until after the more costeffective available commercial and industrial demand resources have been exhausted. The advent of smart thermostats like the NESTTM and potentially implicitly smart loads like electric-vehicle chargers can be expected to increase the available low-cost responsive load in the residential settings [108].

7.2 Aggregation

We have shown that closed loop control of aggregate $T\Delta_0$ thermostatic loads can be accomplished provided a suitable control system which curtails u(k) device for $k = 0, 1, 2 \cdots$. Each control impulse transfers devices between the unresponsive population and the responsive population, altering the responsive population's state $\mathbf{x}(k+1)$ by simply adding the new population's $x_k(k+1)$ response to the input u(k). By combining load curtailment and load release impulses the aggregate response can be shaped to track an arbitrary reference signal r(k), provided sufficient devices are available in both the responsive and background unresponsive population to supply the net change required by each impulse u(k).

Overall the results indicate that an aggregate load model of discrete time thermostats can be used to design such an aggregate load control strategy. But not all controllers designed using conventional methods perform equally well. Proportional controllers and unity-damped controllers, while simplest to implement, tend to be slow to respond and can have stability problems at high load. Pole placement designs tend to result in controllers with steady state errors and/or excessive overshoot. Integral error feedback exhibits the smallest average error as well as the smallest overshoot and are therefore deemed the best controllers studied. The main disadvantage of the integral-error-feedback controller design remains the need to implement a parameter estimation method to reduce the effect of model error on tracking performance.

A potentially useful extension to this approach is "symmetric control", which uses all devices in the unresponsive population instead of only devices that are on. This control approach allows the utility to increase loads by turning devices on as easily as it can decrease load by turning devices off. In some cases, this approach may be more practical for utilities to deploy, and offers the added benefit of addressing possible privacy concerns resulting from any strategy that requires the utility to know whether one particular device is actually on before choosing which devices to signal. In addition, it offers the utility an opportunity to aggregate load control for ancillary services, which may require both load up and load down regulation.

In the cases when we seek full control over the load we must make two important assumptions regarding load curtailment strategies.

- 1. Devices are selected regardless of their current state.
- 2. The load is observed based on the number of devices that remain on rather than the number of devices that are turned off.

The demand response strategy is then described by using $\mathbf{h} = [\bar{R}, 1 - \bar{R}]^T$ and $\mathbf{c} = [\bar{q}, 0]$, where $\bar{R} = \frac{\bar{r}_{off}}{\bar{r}_{on} + \bar{r}_{off}}$ is the population average duty cycle, and \bar{q} is the population average load of a single device. The system is controllable when

$$|C| = \begin{vmatrix} \bar{R} & \bar{R}(1 - \rho_{on}) + (1 - \bar{R})\rho_{off} \\ 1 - \bar{R} & \bar{R}\rho_{on} + (1 - \bar{R})(1 - \rho_{off}) \end{vmatrix}$$
$$= \bar{R}\rho_{on} - (1 - \bar{R})\rho_{off} \neq 0$$

or when

$$\bar{R} \neq \frac{\rho_{off}}{\rho_{off} + \rho_{on}},$$

a condition that is satisfied when $\sigma_{on}, \sigma_{off} > 0$; i.e., the thermal properties of the population are diversified. The system is observable when

$$|O| = \begin{vmatrix} \bar{q} & 0\\ \bar{q}(1-\rho_{on}) & \bar{q}\rho_{off} \end{vmatrix} = \bar{q}^2 \rho_{off} \neq 0$$

which is always true when thermostatically controlled load is active.

In future work we anticipate examining parameter identification strategies to facilitate the implementation of practical load control at the utility scale. In addition, adaptive control, model-predictive control and optimal control strategies should be considered. The latter seems particularly interesting in the context of optimal area control and balance frequency regulation objectives with periodic redispatch of load control resources to keep the maximum number of loads available for regulation services over time.

7.3 Regulation

Using the closed-loop system model GK we can compare the proposed control policy's contribution to improving intra-area control robustness to uncertainty in the availability of fast-acting demand response at the time of a generation contingency. Uncertainty in controllable load can be very large and results from significant diurnal and seasonal variations in the load composition [109]. Fast-acting demand response is typically associated with heating, cooling, and more recently, vehicle charging loads because they are flexible in the short term and are usually a significant fraction of the total load at peak times when generation contingencies pose a greater threat to overall system reliability.

7.3.1 Robustness to FADR Uncertainty

The robustness of the \mathcal{H}_2 -optimal control policy relative to the conventional ACE control in the presence of highly varying levels of FADR is apparent from Figure 5.11. This result is highly significant, particularly when used in the context of FADR to mitigate high penetration of renewables. Increasing renewable resources are associated

with declining system inertial response [110] and can lead to more rapid degradation in system stability. As previously discussed, increased FADR can also contribute to deteriorating system stability margins [94]. So while FADR can mitigate renewable intermittency in terms of temporarily relieving thermal generating units from having to quickly ramp, it cannot be concluded that FADR necessarily improves short term system stability without additional measures being applied to the area control policy. The initial results for high-levels of FADR suggest that this is indeed the case and that at the very least the conventional ACE control policy must be reexamined as increasing levels of uncontrollable renewable generation are used and FADR is employed to mitigate the impact.

A further consideration is the selection of the FADR design condition. In this study a 5% FADR level was used. The performance of the new control policy using this design condition is quite robust for a wide range of FADR levels. However, it should be recognized that the new control policy is optimal only when the FADR level is close to 5%. At other levels of FADR availability the performance would be suboptimal, although it still remains much better than the conventional ACE control policy, as the cost and energy savings in Table 5.1 demonstrate. This suggests that careful consideration should be given to the choice of FADR design conditions, especially with respect to (1) the probability distribution of FADR levels over the course of time, (2) the probability of a generation contingency occurring over the course of time, and (3) the relative cost impacts of those contingencies.

It is significant that the new control policy relies only on measurement of import/export power from the control area. For the control policy to be effective, these measurements must be made at very high rate compared to the SCADA measurement rate of 0.25 Hz for ACE. Based on the very fast response rate of the loads, a measurement rate similar to that of phasor measurement units (PMUs) may be necessary for the proposed area control policy. Most PMUs can sample phase angles at 60 Hz, and are capable of point-on-wave measurements in excess of 1000 Hz. However, the control design would have to consider the communications latency from the remote PMUs to the control area's data concentrator [111]. PMU technology and availability is evolving rapidly and the North America Synchrophasor Initiative (NASPI) has considered the possibility of such a requirement in the design and implementation of the current synchrophasor network [112].

7.4 Dispatch

The significance of the results shown in Figure 6.3 cannot be understated. First we observe that when the marginal price of energy a is much larger than the marginal price of ramping c, the optimal response is very similar to the conventional dispatch strategy, giving us some assurance that today's operations are very nearly optimal. However, when $a \ll c$, today's hourly dispatch strategy is not optimal. As the fraction of cost attributed to energy decreases relative to the cost attributed to ramping, we see that ratio $\omega = \sqrt{\frac{a}{c}}$ decreases and the value of changing the dispatch strategy increases dramatically. In the limit of a very high renewable scenario the savings achievable using the optimal dispatch strategy can be extremely significant. Failure to adopt an optimal dispatch such as the one proposed could result in major and likely unnecessary costs. Utilities will inevitably find it necessary to mitigate these costs, either by reducing the amount of renewables, by increasing the revenues from their customers, or by developing some kind of optimal resource allocation strategy such as the one proposed.

A sensitivity analysis of the savings as a function of the marginal price of ramping c shows that the savings are not overly sensitive to changes in our assumption of the cost of ramping scarcity. Figure 7.4 shows that for a 50% decrease in c, we observe a 10.3% decrease in savings, while a 50% increase in c results in a 3.9% increase in savings. This suggests that the savings from employing the optimal dispatch strategy is quite robust to our uncertainty about the marginal price of ramping resources.

In any financially sustainable future scenario, we must consider how the longterm average costs and fixed costs are recovered under the pricing mechanism. We have implicitly assumed in this study that renewable generation and utilities cannot sustainably continue employing complex power purchasing agreements and subsidies to hedge against energy price volatility. Instead all parties should come to rely on separate real-time pricing mechanisms for energy, power and ramping response of the resources they control.

Shifting revenue from resource allocation mechanisms based primarily on energy resource scarcity to ones based primarily on flexibility resource scarcity can be expected to have a significant impact on the cost of subhourly resource dispatch. The optimal strategy for low renewable conditions very closely matches the strategy employed today when moving hour-to-hour from one scheduled operating point to another. Indeed, the optimal dispatch strategy does not offer any significant cost savings



Figure 7.4: Sensitivity of savings to marginal price of ramping resources.

when overall pricing is dominated by energy resource scarcity.

However, as increasing amounts of renewables are introduced, the scarcity rents may shift from energy to flexibility resources. The optimal subhourly dispatch strategy may be expected to change with increasing emphasis on avoiding high ramp rates over sustained periods at the expense of maintaining a constant power level over the hour.

The relationship between existing price signals for various grid services and the three principal price components needed to implement this optimal strategy requires further investigation. It is evident that the marginal price a represents a linearization of the energy price itself at the current operating point. But it is not clear yet whether and to what degree the marginal prices b and c can be connected to any existing price signals, such as the capacity price or the price of ancillary services such as frequency regulation resources, generation reserves, and demand response. The links do suggest themselves based on both the resource behaviors and physical dimensions of the parameters. However, it is not yet certain whether this will be simply a matter of obtaining a linearization of the services' cost functions at the appropriate operating point.

Additionally, it is instructive to note that the marginal price of redispatched power

b is not important to the optimal dispatch strategy, insofar as the parameter does not appear in Eq. 6.2. This leads one to conclude that to the extent capacity limits do not affect either energy or ramping scarcity rents (or are already captured in them), the marginal cost of additional resource capacity is never considered for optimal subhourly dispatch control. This is consistent with the expectation that sunk costs should not be a factor in the selection of which units to dispatch at what level, at least to the extent that these costs are not entering into the energy or ramping costs.

In the presence of significant renewables, the energy marginal cost does not entirely reflect the grid condition without considering the cost of ramping up and down services. Therefore, the energy price cannot be solely used as a control signal to the generation and load units to achieve the optimal utilization of resources. In order to quantify the value of ramping product we suggest using a market framework in which flexible generation and load resources compete to sell their ancillary service products at the bulk electric system level. As renewable level rises the marginal price of energy decreases (smaller a value) because renewables are zero-generation cost resources, but the marginal price of ramping increases (larger c value) because the system requires more flexibility to handle the generation variation. In long run, inflexible units get retired and more flexible units are built to support the renewable integration since flexibility will be a revenue source rather than energy.

The availability of high renewables can lead to situations where low cost energy is being supplied to areas with high cost flexibility resources through constrained interties. The optimal strategy avoids dispatching these high cost flexibility resources to the extent possible by reducing the ramping schedule. The more transmission capacity available, the lower the overall cost, but we note that even when the system is constrained, the cost of optimally dispatching flexibility resources can be significantly lower under the high renewables case than under a low renewables scenario.

7.5 Ramping Market Price

Wholesale electric energy markets have been used widely since they were first introduced in the 1980s. The market design is conceptually relatively simple and is illustrated in Figure 7.5, where renewables have lower marginal cost than fossil units. The supply and demand curves are constructed by summing the marginal cost functions of all supply and demand units when ordered by price. As a result, when the clearing price is obtained, only the supply units with marginal costs below that price



Figure 7.5: Energy market with supply curve (red) and demand curve (blue), with the price P_C at which the export ΔQ is realized.

and demand units with reservation prices above that price are operated.

The key feature of this mechanism for the purposes of transactive control between control areas that if a specific difference ΔQ between supply and demand is desired (e.g., a specific import or export quantity is to be achieved) then we can directly compute the price P_C at which that import or export is realized.

Throughout this thesis ramping supply markets are used assuming (1) that they exist and (2) that they operate in a similar manner. In this section we explore whether these two assumptions are true and to the extent that they are not, what must be done to see them realized.

We illustrate a wholesale ramping market in Figure 7.6. In this market, demand response from loads are the least costly to deploy per unit of ramp rate, followed by storage units, and fossil units are the most costly to deploy. The required rate \dot{Q}_C is obtained from the real-time system operation, and units that have contributed to the ramp response are compensated at the price R_C . All the units with ramping prices below R_C are required to provide the ramp response \dot{Q}_C .

At this point it remains unclear how to design a market clearing mechanism that generates the separate marginal price signals identified in the optimal dispatch strategy in Chapter 6. This remains an important area of ongoing research.



Figure 7.6: Ramping market with supply curve (red) and demand curve (blue), with the price P_C at which the export ΔQ is realized.



Figure 7.7: Price-based control over-actuation of aggregate load

7.5.1 Unified Market Design

Throughout this thesis we have considered problems where energy, power and ramping are controlled jointly. We have made the assumption that this is necessary based on the observation that $E(t) = \int_0^t L(x) dx$ and $R(t) = \dot{L}(t)$, where E is the total energy consumed by the load L at the time t, and R is the rate of change of the load Lat the time t. We then recognized that there can be only one controllable resources in the aggregate at any given timescale, as shown in Figure 7.7, using price control gains K_E , K_Q and K_R . Using independent prices for energy, power, and ramp as control inputs at any given timescale to control the system leads to over-actuation of the system-there are three control inputs $(P_E, P_Q, \text{ and } P_R)$, but there is only one degree of freedom (Q). Consequently we must consider a unified price-based control



Figure 7.8: Market-based unified price-based control of aggregate load

where there is a single price, which effectively controls the joint energy, power and ramp behavior of the load, as shown in Figure 7.8.

The unified price is given as

$$P(s) = B(s) \left[\frac{1}{s} M_E(s) + M_Q(s) + s M_R(s) \right],$$

where M_E , and M_Q and M_E are the energy, power, and ramp price-discovery mechanisms. The assumption in the literature is that these mechanisms are independent, but the results of this thesis suggest that it cannot be so.

The energy and ramp market mechanisms are well separated in frequency domain, and the results of the optimal dispatch function support this conclusion. However, the bids into the energy market and the bids into the ramp market are not independent, as is often recognized when one attempts co-optimization of the two. In the aggregate, the ramp resources are determined by the cleared energy resources. Thus there is only one set of coordinated bids, B, which come from the aggregated loads and must be cleared through all the markets simultaneously, with each market influencing the response in a separate response band in frequency domain.

What remains to be determined is the exact design of these bid clearing mechanisms so that they jointly determine a unified price. Specifically, we do not have transfer functions that adequately describe the general transfer functions of these markets such that we can bring control theory to bear on the system design problem. In Appendix B we examine the stabilization of a "tatonnement" transfer function for bilateral negotiated price discovery. The study of transfer functions for multilateral and auction-based price discovery processes is a significant open area of research for transactive control systems.

7.6 Recommendations

In summary, we have identified the following ten recommendations for future work in transactive control research.

- **Recommendation 1:** Utilities need to identify the conditions under which price instability can emerge under high renewables and implement either market and/or distributed resource control mechanisms to mitigate them.
- **Recommendation 2:** Strategic bidding may be necessary for resources to elicit nonzero price signals. However, strategic bidding at the retail level entails an entirely new class of regulatory oversight that is not currently envisioned in most jurisdictions.
- **Recommendation 3:** The benefits of automated metering infrastructure for residential customers have yet to be studied in detail or realized in practice, either with indirect price-based or direct load control mechanisms.
- **Recommendation 4:** Symmetric control, which uses all devices in the uncontrolled population instead of only devices that are on, needs to be considered as a possible control approach that allows the utility mitigate renewable intermittency.
- **Recommendation 5:** Adaptive control, model-predictive control and optimal control strategies should be considered for utility-scale resource dispatch, particularly in the context of optimal area control and balance frequency regulation with periodic redispatch of distributed resources to maintain provision of sufficient distributed resources for regulation services.
- **Recommendation 6:** Further examination of the choices of fast-acting demand response (FADR) designs is needed, especially with respect to (1) the availability of FADR over time, (2) the probability of a generation contingency occurring over time, and (3) the relative cost impacts of those contingencies.
- **Recommendation 7:** Distributed resource control designs that depend on phasor measurement units (PMUs) need to carefully consider the communications latency from the remote PMUs to the control area's data concentrator before being considered as an element of or alternative to transactive control systems.

- **Recommendation 8:** The relationship between existing price signals for various grid services and the energy, power, and ramp price components needed to implement optimal dispatch strategies need to be investigated. Quadratic cost functions allow a linearization of these prices at the current operating point. But the marginal price of ramping in particular has yet to be connected to any ancillary services market designs or existing cost functions.
- **Recommendation 9:** The problem of how to design a general transactive market clearing mechanism that discovers distinct marginal prices for energy and ramping remains an important unresolved question.
- **Recommendation 10:** The exact design of market mechanisms that produces a unified price signal is unresolved. Specifically, we do not have transfer functions that adequately describes the power response as function of price in the short term such that we can analyze system performance in general. The study of transfer functions for multilateral and auction-based price discovery mechanisms is an important open area of research for transactive control systems.

Chapter 8

Conclusions

The results of this thesis generally show that it is possible to establish both a common transactive basis for control at over a wide range of scales, as well as achieve locally advantageous implementations of transactive control that in many cases outperform the conventional controls used today. This is achieved for example, by leveraging the flexibility of millions of small load devices to relieve the burden on flexible generators to respond to ramping demands stemming from the inflexibility of other generators. Similarly, the results show how dispatch flexibility can be used to both guide more robust and cost-effective frequency regulation response, as well as maintain optimal scheduling from one hour to the next.

In this thesis we have examined four important areas of transactive control system design that will be necessary to the eventual implementation of a more comprehensive transaction energy system. These are (1) aggregate demand response observation and (2) aggregate discrete-time cyclic load control, (3) optimal frequency regulation with area import/export tracking, and (4) optimal area dispatch.

An *ab initio* aggregate load model of fast-acting controllable thermostatic electric loads operating under the transactive control paradigm that corresponds to the Random Utility Model commonly used in the economics of consumer choice. The proposed model is verified with empirical data collected from field demonstration projects and shown to perform better than alternate models commonly used to forecast demand in normal operating conditions. The results suggest more broadly that (1) existing utility tariffs appear may be unable to incentivize sufficient fast-acting demand response to mitigate the impact of high renewables, and (2) existing load control systems may be easily saturated and become unstable if utilities simply close the control loop using only real-time energy prices.

- An aggregate load controller for discrete-time zero-deadband thermostats, a general controller design that allows various aggregate load control strategies to be explored, and specific controller that allow large-scale control of thermostatic loads that have high endurance. The aggregate load controller is studied for a variety of conventional control designs and is used to design a stable discrete-time closed-loop aggregate load controller for a utility-scale demand response dispatch system. The new controller is shown to be stable, controllable, and observable. It is tested using a large-scale agent-based model of residential heating loads, and works equally well with both direct and indirect load control systems.
- A frequency regulation strategy using an \mathcal{H}_2 -optimal controller for control areas in bulk electricity interconnections that is suited to jointly controlling generation and demand response in areas that have a high penetration of both intermittent renewable resources and fast-acting demand response. The mechanism offers significant cost savings in systems with very high levels of renewable resources. The results show that the optimal controller outperforms the conventional ACE control policy by 1) providing faster return to the schedule under varying demand response levels, 2) reducing the cost of calling up reserve units for regulation services, and 3) minimizing deviations from the global surplusmaximizing schedule.
- An optimal dispatch that considers both the cost of energy and the cost of ramping simultaneously and exploits significant cost savings opportunities in systems with high levels of renewable generation. The optimal price-based control solution responds to both a short-term price of energy for demand dispatch, as well as a short-term price of power for ramp response. The result is (1) a formal method to compute the optimal sub-hourly power trajectory for a system when the cost of energy and ramping are both of the same order, (2) an optimal resource allocation strategy based on this optimal trajectory, and (3) a simulation method to evaluate the cost savings potential of using the optimal trajectory when compared to the conventional sub-hourly dispatch used in today's system operation.
8.1 Principal Contributions and Findings

(1) Demand Response can be modeled as a logistic demand curve for short term electricity consumption derived from the first principles of controllable thermostatic electric loads operating under the transactive control paradigm. We have shown that this model corresponds to the Random Utility Model commonly used in the economics of consumer choice. The model's performance is compared to results from two US Department of Energy demonstration projects in which short-term demand response data were obtained. We found that the random utility model predicts the total demand response to smaller price fluctuations very well, but that model performance degrades as the magnitude and frequency of price excursions increases and as the diversity of load states decreases. We conclude that the random utility model is suitable for demand response studies that utilize steady state conditions for most situations with only infrequent and modest price excursions.

In its present form the random utility model provides a robust framework that is well-founded in the engineering principles of how thermostatic devices behave in price-based control environments. By joining the engineering and economic behavior of such devices, the random utility model is set to become an essential element in the planning, design and eventual deployment of large-scale load control strategies.

(2) Load Aggregation at the utility scale was developed in the direct load control problem for the situation in which the controlled loads employ discretetime zero-deadband $(T\Delta_0)$ residential thermostats. We showed how $T\Delta_0$ thermostats allow utility dispatchers to use small adjustments to the consumer's setpoint to modulate the total load with greater precision than is possible using current setback control of thermostats with non-zero deadbands. These new digital thermostats can serve as the basis for highly accurate direct load control systems, as well as price-based indirect load control systems.

A new linear aggregate load model was found based on the dynamics of load states and its fundamental characteristics were used to consider a number of benchmark aggregate load control designs from first principles. We used this model to design a simple closed-loop aggregate controller for a discrete-time utility-scale demand response dispatch system that is compatible with the requirements for both direct and indirect load control systems and tested the control design using a large-scale agent-based model of demand response based on thermostatic loads. We showed that the aggregate controlled load is stable, controllable, and observable, and exhibits both the transient and steady-state response characteristics necessary to serve equally well for utilities that seek to control load using either direct load control or price-based indirect demand response strategies.

- (3) Optimal regulation using an \mathcal{H}_2 -optimal approach was synthesized to obtain the control policy for control areas in bulk electricity interconnections. The approach is suited to controlling both generation and demand response in areas that have a high penetration of both intermittent renewable resources and fastacting demand response. The implementation of the \mathcal{H}_2 -optimal control policy is compatible with, and indeed depends on the existing methods of transactive control 5-minute dispatch strategy. The transactive \mathcal{H}_2 -optimal area control policy was shown to be superior to the conventional ACE control policy in that it is (1) significantly more robust to uncertainty in the amount of fastacting demand response that is available, (2) always less costly and less energy intensive, and (3) minimizes deviation from any surplus maximizing schedule.
- (4) Optimal dispatch was solved using a strategy that considers both the cost of energy and the cost of ramping simultaneously, which leads to significant cost savings in systems with high levels of renewable generation. For the WECC 2024 common case the savings can exceed 40% of total operating costs in the high renewables scenario. As the bulk power interconnection marginal resources shift from primarily dispatchable non-zero marginal fuel cost resources (e.g., natural gas) to primarily non-dispatchable renewable resources (e.g., wind, solar) we expect a steady shift in bulk system revenue from energy scarcity rent to ramping scarcity rent. While the total revenue must remain largely the same for financial sustainability, the scarcity pricing mechanism must change.

8.2 Future Research

As discussed in Chapter 7 the results achieved do not provide all the elements necessary to realize the vision of a fully transactive system. Significant work remains at all physical and temporal scales. Notably absent is the computational infrastructure required for transactive implementations. Also significant is that very few pilot projects are planned, particularly addressing coordination by higher level system functions such as control area dispatch or inter-area scheduling. With regard to the specific systems discussed in this these, the following future research opportunities have been identified.

8.2.1 Demand Response

Future work on short-term aggregate demand response must investigate models that account for varying effective duty cycles for large populations of responsive loads and account for the effect of large fast changes in prices. Methods based on the entropy of the population states seem to offer significant promise.

The random utility model supports previous claims that additional research will be required to mitigate the potential instabilities that may emerge when employing real-time pricing signals for closed-loop feedback control of fast-acting residential demand response. This work will necessarily require a contribution from the field of control theory, while maintaining strong support from economists with an interest in mechanism design.

The model also highlights emerging challenges for tariff design and rate approval processes, particularly in cases where significant distributed generation and storage resources participate in price-discovery alongside fast-acting demand response. The question of incentive-compatible retail market design can be expected to become more important as new tariffs and rate structures are developed by utilities and regulators.

8.2.2 Aggregate Thermostatic Load Control

Future work on thermostatic control needs to develop parameter system identification strategies that facilitate the implementation of practical load control at the utility scale. In addition, adaptive control, model-predictive control and optimal control strategies should be considered. The last seems particularly interesting in the context of optimal area control and balance frequency regulation objectives with periodic redispatch of load control resources to keep the maximum number of loads available for regulation services over time.

8.2.3 Regulation

The \mathcal{H}_2 -optimal control design has considered only local disturbances, viz., loss of generation originating within the same generation control area. It will be necessary to consider a wide range of additional disturbances including

- 1. An internal loss of load (note that this is not equivalent to a negative loss of generation because the responsive resource mix changes),
- 2. An external loss of generation or load,
- 3. A loss of a tieline between generation control areas, and
- 4. Rapid ramp up and down, both internally and externally, due to unexpected changes in renewable resources.

In addition, the new control policy must address the impact of eliminating direct observation of system frequency from the measurement. The role of the secondary generation is to cancel the steady-state frequency deviation and bring each area's net exports back to the scheduled value, either with ACE or \mathcal{H}_2 -optimal control. A component of the \mathcal{H}_2 -optimal area generation control minimizes the frequency deviations so it will cope with some, but not necessarily all of the steady-state frequency deviation. It seems unlikely that such a change to the area control policy could go unnoticed, particularly in the event that system inertia and damping change significantly in a short time. Although generation droop remains in effect for all controlled generating units that do not have a master controller, the slow diminution of droop-only units could lead to situations where there is slow or inadequate control of system frequency even though there is very authoritative control of inter-area power exchanges.

This study examined an extreme case in which 75% of the generation was uncontrolled renewable and only 25% of the generation was regulated using the area control policy. For one thing, such a great percentage of renewables means the system does not have enough inertia to deal with both renewable and load uncertainty, so the existing AGC system is unable to adequately control the system. Although we considered a relatively low inertia systems, we expect that much lower total system inertia should be considered (perhaps as low as M = 2 seconds). With such low system inertia it seems even more likely that control areas will require an augmented or entirely new control policy, and that the advantage of \mathcal{H}_2 -optimal ACE control may be more evident.

In North America, balancing authorities are scored based on how well they contribute to interconnection frequency regulation needs while tracking their export schedule. The optimal response as presented here does not consider how often "zerocrossings" of nominal frequency occur or how noisy frequency control is. Future studies of optimal-ACE policies considering fast-acting demand response control design will need to also consider the control performance standards CPS-1 and CPS-2 [91].

8.2.4 Dispatch

The principal consequence of using the proposed dispatch strategy for control areas considering both energy and ramping costs is an annual cost savings in WECC projected to exceed US\$150B by the year 2024. Extrapolated roughly to all of North America, this may result in savings approach US\$500B annually. It is also clear that the use of energy-only market designs runs counter to the results of this study. Flexilibity resource markets may become increasingly important as ramping resources become more scare. This may be true even in regions that are not dominated by local renewable generation but adequate transmission capacity is available for renewables in remote regions to displace local dispatchable generation. This may give rise to a new set of challenges for utility and system operators as they seek a revenue model that not only provides for operating costs, but also maintains the coupling between retail demand response and wholesale supply and retail delivery constraints. If the cost of the wholesale system becomes increasingly dominated by ramping resource constraints, while retail continues to use energy prices to encourage consumer efficiency, then retail behavior will be not affected as much by short-term wholesale price fluctuations. This trend runs against the desire for more engaged consumers who can respond to system conditions in real time. Clearly a new utility revenue model is needed if the transformation to a high renewable *modus operandi* is to occur successfully in the coming decades.

8.3 Summary

Taken as a whole the results of this thesis show that one can incorporate transactive energy technology into today's system operations without simultaneously transforming all aspects of system operation in all parts of the system. Each solution can be independently deployed profitably and successfully in a heterogenous operating environment while maintaining system reliability, security, and economic stability.

But the advantages of integrating these solutions together grow with the increased use of transactive technologies, with greater availability of renewable energy resources, and with greater participation by consumer-based assets in system operation. In the final analysis, transactive control offers the greatest potential for consumer benefits, the most flexibility approach to evolving the utility business model, and most importantly the most effective means of addressing the global impact of meeting the energy demands of the 21st century economy.

Appendix A Demand Elasticity

Over the years, research has consistently shown that demand response (DR) can participate in all electricity markets, including energy, capacity, and regulation [28]. Transactive control and Powermatcher were proposed and demonstrated in the field as approaches that could unify the scheduling, dispatch and control of all distributed energy resources, including DR, on the retail side [38]. Since then there is growing interest in the broader concept of transactive energy in both Europe and North America [113]. In addition a number of important technical contributions have been made to support transactive energy systems, including the design of device controllers [73], real-time pricing [114], and retail market designs, in various jurisdictions in North America and elsewhere.

However, the fundamental behaviors and properties of transactive systems remain a largely open research area. From the viewpoint of power system and control engineering, this is a critical gap and to this day it stands as a significant barrier to the widespread adoption of transactive control systems—utilities are hesitant to adopt a new control strategy in the absence of a clear and validated mathematical framework to study and prove the stability, robustness, and reliability against all hazards.

One important aspect of this gap is the nature and role of DR elasticity of energy, power, and ramp resources in electricity markets. This appendix briefly presents a result that may be of significance to researchers in transactive energy and transactive control insofar as it establishes a strong and potentially useful connection between the elasticity of energy, power and ramp response resources in electricity markets, both wholesale and retail. This relationship is examined and its implications are discussed briefly with respect to the design of DR controllers, utility and demand aggregator business models, and regulatory oversight of electricity markets, especially in the context of retail competition.

A.1 Analysis

Consider the energy consumption q(p,t) at the energy price p and time t, the price varying also in time. The power demand is

$$s(p,t) = \frac{\partial q(p,t)}{\partial t}$$

and the ramp rate is

$$r(p,t) = \frac{\partial s(p,t)}{\partial t} = \frac{\partial^2 q(p,t)}{\partial t^2}.$$

We know the energy demand elasticity is

$$\eta_q(p,t) = \frac{p}{q(p,t)} \frac{\partial q(p,t)}{\partial p}$$

and if we assume that short term energy elasticity (viz., 1 hour or less) is the constant η_q , then we must have

$$\begin{split} q(p,t) &= \frac{p}{\eta_q} \frac{\partial q(p,t)}{\partial p} \\ \frac{\partial q(p,t)}{\partial t} &= \frac{\partial}{\partial t} \left(\frac{p}{\eta_q} \frac{\partial q(p,t)}{\partial p} \right) \\ \eta_q s(p,t) &= \frac{\partial p}{\partial t} \frac{\partial q(p,t)}{\partial p} + p \frac{\partial^2 q(p,t)}{\partial p \partial t} \\ &= \frac{\partial q(p,t)}{\partial t} + p \frac{\partial}{\partial p} \frac{\partial q(p,t)}{\partial t} \\ &= s(p,t) + p \frac{\partial s(p,t)}{\partial p} \\ (\eta_q - 1) s(p,t) &= p \frac{\partial s(p,t)}{\partial p} \end{split}$$

and thus the power demand elasticity

$$\eta_s = \frac{p}{s(p,t)} \frac{\partial s(p,t)}{\partial p} = \eta_q - 1$$

By similar reasoning we find that the ramp demand elasticity is

$$\eta_r = \frac{p}{r(p,t)} \frac{\partial r(p,t)}{\partial p} = \eta_s - 1$$

and we identify a previously unrecognized but potentially important relation between the energy, power and ramp response elasticities with respect to energy price:

$$\eta_q = \eta_s + 1 = \eta_r + 2 \tag{A.1}$$

We make the following observations based on Equation (A.1).

- 1. When any one of the ramp, power, or energy demand elasticities is constant in time then they all are constant in time. Thus it is only necessary to observe one constant elasticity to know them all.
- 2. In the limit of absolutely inelastic energy demand, power demand elasticity is unitary. This result implies that even though energy demand may be nearly inelastic, power and ramp demand can remain highly elastic.
- 3. Ramp demand elasticity is always highly elastic. This suggests that for ramping DR resources, the supplier of ramp resources never has market power.

A.2 Discussion

The absence of concurrent energy, power, and ramp pricing and DR data to validate Equation (A.1) is noted. We believe those with access to field data on DR elasticity should examine their data to confirm whether and under what conditions Equation (A.1) holds. In addition, we suggest the following research questions be considered in light of Equation (A.1) and the observations made above.

A.2.1 Device Control

If a device that demands energy is designed to elicit information from the consumer for the purposes of developing a demand curve, then Equation (A.1) implies that it is sufficient to obtain this information for only one of energy, power, or ramp responses and the other demand curves may be computed directly. It is not necessary to design a separate transactive control strategy for the energy, power, and ramp behavior of the device.

In addition, this result suggests that policies to prevent resources from bidding concurrently in energy, capacity and regulation markets may not conform to the underlying dynamics of transactive systems. Devices cannot decouple these behaviors from each other even if they wanted to. This fits well with markets that concurrently clear energy, capacity, and regulation prices and ensures that no device is provided conflicting or inconsistent price signals from the markets.

A.2.2 Business Models

Utilities and load aggregators must consider the market power implications of Equation (A.1), insofar as they will often have monopoly market power as suppliers of energy DR resource while having monopsony market power as consumers of ramp response resources. We note in particular that because load is likely to supply ramping resources its market power is expected to be as low as it is for energy demand, while power response resources will likely be close to unitary elasticity. This is particularly important as utilities begin to shift revenue away from energy-based tariffs toward tariffs based on products and services that have greater downward substitutability.

However, if customers are purchasing ramping DR to mitigate the intermittency of their own on-site renewables such as solar photovoltaic (PV) panels, then their market power increases. The presence of large numbers of such PV- and DR-enabled consumers can be expected to create a rich and flexible retail market in which resources can be coordinated using only price signals. If the utility uses a business model based on revenue from trading activity rather than revenue from sales of net energy, capacity scarcity or ramping services, then it is likely to see greater stability in net revenue by becoming a market maker rather than a provider of last resort for these resources.

A.2.3 Regulatory Oversight

From the regulatory perspective, the utility as a market maker presents a new challenge. Historically, regulatory bodies have focused on authorizing retail tariffs because the utility is a natural monopoly. If the utility is a market maker reimbursed only for the cost of operating the system that enables trading and delivery among market participants, then the regulator now ensures that the utility's market and operation costs are fair and equitable.

However, the regulator is now also concerned with whether the market is being manipulated by any of the participants. As a result, regulators must work with utilities to determine whether any customer or load aggregator is exerting excessive market power. The methods for this kind of monitoring are well-known from other markets. But we expect that certain particulars will be unique for retail electricity markets, particularly in light of the conditions that give rise to Equation (A.1). This problem is complicated by the tight coupling of energy, power, and ramping, as a result of which mitigating the utilities' energy monopoly power may not be sufficient to mitigate their monopsony market power for ramping services, or vice-versa.

A.3 Conclusion

Transactive energy facilitates integrated economic and technical scheduling, dispatch and control of demand response resources as intermittent renewable energy grows and challenges the economic viability, security and reliability of bulk electricity systems. We have shown that there exists an important and simple relationship between the energy price elasticities of energy demand, power capacity demand and ramping resources. Data collection from existing demand response systems is needed to validate this result. But the strong coupling of energy, power, and ramping response elasticities may have important consequences on how we design, deploy, and operate demand response controls, on which utility business models are preferred, and on how we adapt our regulatory oversight mechanisms to better monitor transactive energy systems.

Appendix B

Price Negotiation Convergence

Indirect dispatch systems use incentive signals such as real-time prices to "call" demand response. Most of these systems use day-ahead price signals [115]. Fasteracting 5-minute real-time pricing was also demonstrated successfully in the Olympic and Columbus studies. However, in all such systems computing the incentive signal to be dispatched can be a challenge. In particular, price-feedback systems have been shown to be potentially unstable when they are based on previous responses [82]. In the case of the 5-minute real-time pricing system, a retail double auction was used in which consumer bid prices above which they would forgo consumption for the next five minutes. The advantage of using auctions is that by eliminating the time delay in the feedback, a significant source of the system instability is mitigated.

Unfortunately, auction-based price discovery mechanisms are not always feasible or desirable. In the Pacific study an iterative price-discovery approach was proposed as an alternative to auction-based mechanisms [116]. In this paper we discuss the technical considerations regarding negotiated price-discovery mechanisms when applied to demand response dispatch problems. We address one of the principal problems in fast-acting indirect demand dispatch; i.e., computing the incentive signal necessary to achieve a particular level of demand response. We specifically examine the theoretical basis for a real-time negotiation-based price-discovery mechanisms such as the one tested in the Pacific demonstration and propose an approach for ensuring that such mechanisms robustly and reliably find the retail price at which supply will equal demand.

B.1 Transactive Price-Discovery

We first examine the technical considerations for utilities that wish to dispatch demand response for loads that present responses that are functionally unknown. When this situation arises, utilities must employ one of several possible mechanisms to discover the dispatch signal that will satisfy the physical constraints on the system. In this section we will consider one such mechanism with the understanding that the principles and methods apply more broadly to any iterative price-discovery mechanism a utility may wish to employ. The main contribution of this section is the derivation of a technique to evaluate limitations on iterative mechanisms used to determine the price at which supply equals demand. We examine this limitation to illustrate how one can use it to design stable real-time price discovery mechanisms for retail electricity markets.

Using arbitrary functional models of supply and demand we can analytically examine the behavior of iterative price discovery mechanisms used in systems that do not employ auction clearing for price-discovery. The simplest iterative price-discovery method is a negotiated price, in which the utility offers an initial hypothetical price p(0) to which potential consumers respond either individually or in the aggregate with a hypothetical quantity q(0). The utility follows up with a second proposed price p(1) to which the consumers respond with a proposed quantity q(1), followed by p(2), q(2) and p(3), q(3) and so on until the utility determines that the process has converged on a price that cannot be changed significantly without increasing the mismatch between supply and demand, or that the process must be stopped due to excessive iteration.

In such a process it is presumed that the functions used by suppliers and consumers to convert quantities to prices and prices to quantities, are respectively the supply and demand curves. These curves are not shared in their entirety with the other party, either because they are considered too business-sensitive to reveal (as is often the case with suppliers) or because they are not explicitly known to the party (as is often the case for consumers). The exchange is also presumed to be so limited that neither party can deduce the other's complete curve, while still sufficient to reliably deduce the dispatch price and quantity at which the two curves intersect.

The simplest possible iterative price-discovery process can be described using the



Figure B.1: Logistic map iteration sequence of price discovery mechanisms in a transactive system for a < -b (left) and a > -b (right).

iterative state equations for quantity and price

$$q(k) = \frac{1}{b}[p(k) - P] + Q$$
 and $p(k+1) = a[q(k) - Q] + P$,

where a and b are the slopes of the supply and demand curves, and P and Q are the clearing price and quantity, to which the negotiation process should converge. When the supply and demand curves are linear functions, we can define the iterative price-discovery process using a linear discrete-time state-space representation

$$\begin{bmatrix} p(k+1)\\ q(k+1) \end{bmatrix} = \begin{bmatrix} 0 & a\\ \frac{a}{b^2} & 0 \end{bmatrix} \begin{bmatrix} p(k)\\ q(k) \end{bmatrix} \text{ for } k = 0, 1, 2, \cdots$$

The stability of this iterative price-discovery mechanism is determined by the magnitude of the roots of the system's characteristic equation $z^2 - \frac{a^2}{b^2} = 0$. Noting that b < 0 < a, we conclude that the negotiation can converge on the clearing price and quantity only when a < -b.

The impact of this stability condition is illustrated in Figure B.1 for two different combinations of a and b, one stable (top) and one unstable (bottom). When the slopes of the supply curve (a) and demand curves (b) in the neighborhood of the clearing price are such that their ratio (a/b) is less than -1, the iterative price discovery mechanism fails to converge on the clearing price and quantity¹.

 $^{^{1}}$ The scenario presented assumes that the negotiation always begins with an opening bid from the supplier. If the opening bid is from the consumer, the iteration direction shown in Figure B.1

This stability condition cannot be generally satisfied for all linear supply and demand curves, specifically when supply is very inelastic and/or demand is very elastic. Neither do we expect it to be satisfied for any general non-linear curves. We can evaluate whether a non-linear system will be stable by considering the following approximations for the supply and demand responses

$$\tilde{p}(k+1) = \alpha q(k)^2 + \beta q(k) + P_{min}$$

and

$$\tilde{q}(k) = Q_U + Q_R \frac{p(k)}{P_{max}}$$

respectively, in the neighborhood of the clearing price and quantity. This approximation is the canonical quadratic map problem based on the recurrence equation

$$x_n = \frac{1}{2} \left(1 - f(n) \left[r^n f(x)^{-1} (1 - 2x_0) \right] \right)$$

where f(n) is the time-domain solution function and $f(x)^{-1}$ is its inverse [117]. This system is known to be meta-stable (i.e. it has no single fixed solution point x_n) for values of r > 3.5, and chaotic for values of r > 4, with closed-form solutions to fknown only for $r \in \{-2, 2, 4\}$.

To determine the stability of a linear negotiated market clearing mechanism when the supply and demand curves are not linear functions, we must evaluate the joint spectral radius for the linearized state space representation

$$\begin{bmatrix} p(k+1) \\ q(k+1) \end{bmatrix} = \underbrace{\begin{bmatrix} 0 & A(q(k)) \\ \frac{A(q(k))}{B^2(p(k))} & 0 \end{bmatrix}}_{G} \begin{bmatrix} p(k) \\ q(k) \end{bmatrix} \quad \text{for } k = 0, 1, 2, \cdots$$

where $(A, B) \in G$ are the first order terms of the Taylor expansions

$$\begin{cases} P(x-q) = P(q) + \underbrace{P'(q)(x-q)}_{A(q)} + \frac{1}{2}P''(q)(x-q)^2 + \cdots \\ Q(y-p) = Q(p) + \underbrace{Q'(p)}_{B(p)} (y-p) + \frac{1}{2}Q''(p)(y-p)^2 + \cdots \end{cases}$$

is reversed and thus the stability condition is reversed as well. This suggests that one approach to addressing stability is to simply reverse the negotiation process when convergence is not achieved. However, this approach does not improve the convergence rate.

of the demand and supply curves about the price and quantity at the iteration k, respectively. Such a system is only stable when the mean spectral radius $\rho(G) < 1$. Thus we can only say that for systems with small amounts of demand response and typical supply curves, convergence can be expected when the supply and demand elasticities at the clearing price and quantity are such that $-B(P_c) < A(Q_c)$. If this is not true, the negotiation will converge only to a boundary region outside of which this condition is satisfied because within that region the process diverges. If the clearing price and quantity are inside the divergence region, then they cannot be discovered by the simple linear negotiation strategy described above.

In the case of logistic demand curves observed in transactive system field demonstrations to date, convergence is possible only when

$$\eta_D > -\frac{1}{\eta_S} \left(\frac{P_c}{Q_c}\right)^2 \tag{B.1}$$

where η_S and η_D are the supply and demand elasticities at the clearing price, respectively. This limits the conditions for which convergence is possible when using linear negotiation stratgies to only relatively inelastic demand curves in the neighborhood of the clearing price and quantity. The more elastic supply is, the less elastic demand must be for the negotiation to successfully converge on a price at which supply will equal demand. As has been observed in the field demonstration data, high demand elasticities do occur during period of constrained supply conditions. This is why we conclude that simple linear iterative negotiated price-discovery mechanisms are generally unsuitable for price-based demand response dispatch systems such as those used for transactive control.

B.2 Stable Mechanism Design

We can use the insights gained from the analysis above to devise a price discovery mechanism using an enhanced negotiating strategy for the utility that will satisfy its objective of quickly finding a price at which supply equals demand. The utility's second proposed price in response to the consumer's initial proposed quantity is augmented with a term that includes the last proposed price, such that

$$p(k+1) = [c - k_p]p(k) + [a - k_q]q(k)$$



Figure B.2: Advanced negotation strategy diagram with quantity constraint tracking

where c is a proportional coefficient for the previous price, and $\mathbf{K} = [k_p, k_q]$ are feedback coefficients that we will use to tune the relative input of the previous price and quantity. The design of this system is illustrated in Figure B.2 and the statespace representation of this advanced negotiation strategy for any reference quantity input r(k) is

$$\begin{bmatrix} p(k+1) \\ q(k+1) \end{bmatrix} = \underbrace{\begin{bmatrix} c & a \\ \frac{a}{b^2} + c & 0 \end{bmatrix}}_{\mathbf{G}} \begin{bmatrix} p(k) \\ q(k) \end{bmatrix} - \underbrace{\begin{bmatrix} 1 \\ \frac{1}{b} \end{bmatrix}}_{\mathbf{H}} \underbrace{\begin{bmatrix} k_p & k_q \end{bmatrix}}_{\mathbf{K}} \begin{bmatrix} p(k) \\ q(k) \end{bmatrix}$$
(B.2)

with the output quantity

$$y(k) = \underbrace{\begin{bmatrix} 0 & 1 \end{bmatrix}}_{\mathbf{c}} \begin{bmatrix} p(k) \\ q(k) \end{bmatrix}.$$

The negotiation strategy design problem for the utility is then reduced to determining the value **K** such that negotiation converges as quickly as possible on the price at which supply equals demand. This "deadbeat" system response requires that the characteristic equation be reduced to $z^2 = 0$, a condition which can be obtained when

$$\mathbf{K} = \left[c - \frac{a^2}{b^2 c(b-1)} - \frac{a}{b} , \ a + \frac{a^2}{bc(b-1)}\right].$$
 (B.3)

An example for three different levels of demand response is shown in Figure B.3, where the demand curve has been linearized in the neighborhood of the clearing price and quantity, as described above. In all three cases, the deadbeat negotiating strategy converges in two iterations to the clearing price and quantity, outperforming the simple linear negotiation strategy for even the stable case. More significantly, the deadbeat strategy converges when the simple strategy fails to converge.



Figure B.3: Simulation of stable (left), marginal (center) and unstable (right) negotiations without (dotted) and with (solid) corresponding deadbeat negotiation strategies.

B.2.1 Demand Response Uncertainty

We note that in Equation (B.3) the slope of the demand curve b is included in the computation of the negotiation strategy parameters of **K**. Uncertainty in b can result in an error in the clearing price and quantity. The demand curve may not be known exactly or it may change from time to time. The utility may wish to employ an enhanced negotiation strategy to reduce the clearing price error that may result from inaccurate estimation of this demand curve parameter b.

A reliable design method based on control theory is to compensate for the unknown demand function by implementing integral error feedback [87] in the negotiation process. This approach adds a third state to the state-space representation in Equation (B.2). This new state represents the accumulated error between the most recent quantity from the consumer(s) and the clearing quantity. This error is then multiplied by a gain k_e and the result is added to the price response p(k + 1). This approach raises the overall order of the system by one and can be expected to decrease the convergence rate compared to the deadbeat negotiation. But integral error feedback has the significant advantage that it compensates for all constant errors in the system, not just demand elasticity estimation errors. The same method used to find **K** above can be used in this case to find the joint feedback gains [**K**, k_e] required to obtain the fastest possible convergence using a linear negotiation. The behavior of this price-discovery mechanism is illustrated in Figure B.4.

The solution for $[\mathbf{K}, k_e]$ using this approach can be found given any reasonable



Figure B.4: Discrete-time system diagram of advanced negotation strategy diagram with demand curve uncertainty

assumption for the value of b. Choosing a value of $\hat{b} = -1$ gives the solution for the feedback gains

$$k_p = 1, \quad k_q = a + \frac{1}{a}, \text{ and } \quad k_e = 1 - \frac{1}{a},$$
 (B.4)

The general solution for the augmented state approach is

$$k_p = 1$$
, $k_q = a + \frac{\hat{b}^2}{a}$, and $k_e = 1 - \frac{\hat{b}^2}{a}$

where \hat{b} is the utility's estimate for the slope b of the demand response curve, as illustrated in Figure B.5. The general solution can be expressed in terms of a utility's price negotiation strategy as

$$p(k+1) = p(k) + (2a+1)q(k) + \left(1 - \frac{\hat{b}^2}{a}\right)\sum_{j=1}^{k-1} q(j)$$

which will converge in a finite time when b < 0 < a but with no particular restriction on the relative magnitudes of a and b.

The closed-loop stability of this solution depends on the magnitude of the error in the estimate of \hat{b} . Specifically, the characteristic equation of this price-discovery solution is

$$z(z^2 - 1 + \frac{\hat{b}^2}{b^2})$$

which suggests that convergence is guaranteed when

$$\sqrt{2b} < \hat{b} < 0. \tag{B.5}$$

The constraint that the magnitude \hat{b} cannot be more than about 40% greater than b



Figure B.5: Integral error feedback negotiation strategy for the same cases as Figure B.3 with a $\pm 10\%$ error in the demand response curve estimate \hat{b} .

is a generally reasonable one for the slope of the demand curve in the neighborhood of the solution price and quantity.

B.3 Conclusions

The dependence of deadbeat negotiation strategy on the utility's knowledge of the demand curve slope b suggests that it is possible to compute the clearing price using a

parametric fit of the demand curve from a very large set of bids instead of negotiating with all the loads individually. Instead of performing an auction clearing as in the Olympic and Columbus demonstration projects the utility can indirectly determined the price at which supply equals demand by computing what the negotiation would produce given the demand curve imputed by the bids without actually performing the negotiation.

This method does assume that the demand curve fits a mathematical function of some type that can be expected to represent the loads' collective behavior most of the time. For example, the demand curve may generally take the form of a logistic function as observed during quiescent periods in both the Olympic and Columbus demonstrations. This function was derived in Chapter 3 and has the form

$$Q = (1 + e^{\alpha + \beta P})^{-1}Q_R + Q_L$$

where α is the unobservable component of the demand response behavior and β is the observable component. The parameters can be estimated using the logistic regression

$$\alpha = \bar{P} - \beta \bar{\xi}$$

and

$$\beta = \frac{\overline{P\xi} - \bar{P}\bar{\xi}}{\overline{P^2} - \bar{P}^2}$$

where $\xi = \ln(Q_U + Q_R - Q) - \ln(Q - Q_U)$. Given such a fit we can estimate the slope of the demand curve at the clearing price

$$\hat{b} = -\frac{\beta Q_R e^{\alpha + \beta P}}{(e^{\alpha + \beta P} + 1)^2},$$

a value that can be readily used to compute the clearing price without performing the full market clearing procedure.

In control theory a non-zero reference quantity r(k) is included in Equation (B.2). This term merits further consideration because it can be used by the utility to change the quantity that the negotiation will converge to. However, this quantity does not necessarily converge to a price at which supply will equal demand. Non-equilibrium values of r(k) may be theoretically interesting, but they likely do not have physical meaning that is useful unless the utility intentionally wishes to increase or decrease the load for some operational reason, such as maintaining a net level of imports or exports. Generally such deliberate manipulation of the negotiation strategy should be regarded with skepticism, particularly if the result would be an economically inefficient price or a power imbalance that results in operational reliability concerns.

Control theory also suggests that when using the integral error feedback negotiation strategy, a better estimate \hat{b} of the demand response slope *b* results in a faster convergence for the negotiation. But the process will always converge regardless of the error. Here again, collecting real-time demand data from customers can contribute to significantly improving the performance of the price-discovery mechanism by providing information needed to obtain a sufficiently accurate estimate of the demand curve slope.

Appendix C

Model Specifications

Parameter	Variable	Distribution	μ	σ	Remarks
Wall conductivity	U_A	Normal	350	50	Truncated at $\pm 3\sigma$
Air heat capacity	C_A	Normal	2000	150	Truncated at $\pm 3\sigma$
Mass conductivity	U_M	Normal	2000	500	Truncated at $\pm 3\sigma$
Mass heat capacity	C_M	Normal	10000	1000	Truncated at $\pm 3\sigma$
Setpoint temperature	T_S	Normal	72	1	Truncated at $\pm 3\sigma$
Design temperature	T_H	None	10	_	
Equipment oversizing	$-\frac{Q_H}{(T_H-T_S)U_A}$	Normal	1.55	0.15	Truncated at $\pm 3\sigma$
Equipment efficiency	ĊOP	Normal	3.0	0.5	Truncated at $\pm 3\sigma$

Table C.1: Aggregate Load Model Parameters

Area		Peak	Energy	Loss
number	Consolidated area	$[\mathbf{MW}]$	[GWh/year]	factor
1	AESO	16095	115061	1.019
2	BCH	12542	69326	1.020
3	PNW = AVA + BPA + CHPD	33384	184103	1.025
	+ DOPD $+$ GCPD $+$ PACW			
	+ PGE + PSEI + SCL + TPWR			
4	NWMT	1898	12163	1.023
5	PAWY	1681	11028	1.013
6	NCA = BANC + CIPB	30626	144848	1.043
	+ CIPV + TIDC			
7	SPPC	2447	15784	1.026
8	ID = IPFE + IPMV + IPTV	4157	19290	1.036
9	UT = PAID + PAUT	8443	39362	1.028
10	CO = WACM + WAUW	5867	34863	1.023
11	LDWP	7789	34129	1.027
12	NEVP	7034	30083	1.045
13	PSCO	8130	41027	1.028
14	SCA = CISC + VEA	26847	119573	1.040
15	AZ = AZPS + SRP	23596	109534	1.026
	+ TEPC $+$ WALC			
16	CISD	5573	26702	1.037
17	IID	1342	4836	1.043
18	PNM	3136	16449	1.026
19	CEF	3255	15452	1.033
20	EPE	2391	11106	1.032

Table C.2: WECC 2024 demand forecast and internal area losses $\left[1\right]$

	Non-dispatchable	Dispatchable	
Area	Intermittent [MW]	Base (invariable) [MW]	generation [MW]
AESO	2275.2	3710	17733
BCH	815.3	3531	17000
PNW	14432.0	5845	36675
NWMT	664.2	1227	1993
PAWY	1315.3	1648	2105
NCA	5092.7	5351	38684
SPPC	800.0	1118	3287
ID	660.3	374	2845
UT	256.5	2183	8136
CO	656.4	1807	4310
LDWP	687.0	89	8727
NEVP	75.7	426	13085
PSCO	2441.1	1616	11645
SCA	6028.1	977	28645
AZ	3220.6	8601	39353
CISD	432.8	34	8558
IID	34.4	1170	1514
PNM	840.3	910	4504
CFE	384.2	697	6600
EPE	1.3	0	3512

Table C.3: WECC 2024 aggregated installed supply capacity [1]

Table C.4: WECC 2024 producer cost and surplus difference for 100% inelastic load (in M\$/year) [1]

	Producer cos	t reduction	Producer surplus reduction		
	Unconstrained	Constrained	Unconstrained	Constrained	
AESO	6642	1797	11421	2820	
BCH	55	149	79	284	
PNW	35	479	-552	588	
NWMT	-260	-236	-1622	-1516	
PAWY	-297	-246	-2513	-2132	
NCA	-393	121	-817	145	
SPPC	-297	-254	-1058	-933	
ID	1873	1907	2630	2696	
UT	453	557	763	997	
CO	1244	1296	2978	3147	
LDWP	2304	2422	2498	2632	
NEVP	-183	-4	-214	-8	
PSCO	-454	-306	-1044	-753	
SCA	5697	6083	7215	7771	
AZ	-4624	-4082	-12111	-10968	
CISD	992	1108	1061	1187	
IID	-213	-192	-1467	-1375	
PNM	-324	-262	-873	-735	
CFE	-521	-287	-873	-506	
EPE	573	622	573	622	
Total	12301	10671	6075	3965	

	Stand	alone	Constrained		
	100% inelastic	95% inelastic	100% inelastic	95% inelastic	
AESO	78.48	78.47	67.51	67.50	
BCH	32.72	32.71	31.31	31.30	
PNW	26.33	26.31	24.64	24.63	
NWMT	1.45	1.44	14.78	14.77	
PAWY	0.00	0.00	11.11	11.10	
NCA	32.14	32.13	31.68	31.67	
SPPC	9.76	9.75	21.29	21.28	
ID	109.06	109.07	32.83	32.79	
UT	35.66	35.62	26.92	26.91	
CO	50.93	50.92	19.19	19.18	
LDWP	97.06	97.04	51.01	51.01	
NEVP	49.45	49.44	49.91	49.90	
PSCO	26.24	26.23	31.62	31.61	
SCA	76.38	76.37	41.27	41.26	
AZ	6.11	6.11	28.10	28.09	
CISD	79.17	79.17	52.90	52.90	
IID	0.01	0.01	13.82	13.81	
PNM	16.58	16.57	27.71	27.71	
CFE	21.43	21.43	33.10	33.11	
EPE	90.20	90.19	57.33	57.33	
Average	41.96	41.95	33.40	33.39	

Table C.5: WECC 2025 production cost per unit in $MWh\ [1]$

Path	From	То	Minimum	Maximum	
number	area	area	$[\mathbf{MW}]$	$[\mathbf{M}\mathbf{W}]$	
P01	AESO	BCH	-1200	1000	
P03	PNW	BCH	-3150	3000	
P08	NWMT	PNW	-2150	3000	
P09	NWMT	CO	-2573	2573	
P14	ID	PNW	-2250	3400	
P16	ID	SPPC	-360	500	
P18	NWMT	ID	-256	337	
P20	ID	UT	-2250	2250	
P22	PNM	AZ	-2325	2325	
P24	NCA	SPPC	-150	160	
P26	NCA	SCA	-3000	4000	
P27	UT	LDWP	-1400	2400	
P30	UT	PSCO	-650	650	
P31	PSCO	PNM	-690	690	
P32	SPPC	UT	-235	440	
P35	UT	NEVP	-580	600	
P36	CO	PSCO	-1680	1680	
P42	IID	SCA	-1500	1500	
P43	LDWP	SCA	-4000	4000	
P44	CISD	SCA	-2500	2500	
P45	CISD	CFE	-800	400	
P46N	NEVP	LDWP	-6000	6000	
P46S	NEVP	SCA	-5000	5000	
P47	EPE	AZ	-1048	1048	
P48	EPE	PNM	-1970	1970	
P49	AZ	NEVP	-10200	10200	
P59	AZ	SCA	-218	218	
P65	PNW	LDWP	-3100	3220	
P66	PNW	NCA	-3675	4800	
P76	PNW	SPPC	-300	300	
P78	UT	PNM	-600	600	
P79	AZ	UT	-300	265	
P80	NWMT	PAWY	-600	600	
PP1	PAWY	UT	-1700	1700	
PP2	IID	CISD	-150	150	
PP3	AZ	CISD	-1160	1650	
PP4	AZ	IID	-160	260	

Table C.6: WECC 2024 model inter-area transfer limits $\left[1\right]$

Appendix D

Simulation Results

Table D.1: Estimated, simulated, and errors of aggregate thermostat load state transition probability ρ using joint PDF (N=normal, Ln=log normal, Log=logistic) using 10⁶ homes and $t_d = 1$ minute.

T_O		N(X)	N(Y)	N(X)	Ln(Y)	Log(X)	N(Y)	Log(X)	Ln(Y)
(°F)		ρ_{off}	$ ho_{on}$	$ ho_{off}$	$ ho_{on}$	$ ho_{off}$	$ ho_{on}$	ρ_{off}	$ ho_{on}$
	Est	1.00	0.44	1.00	0.44	1.00	0.43	1.00	0.43
5	Sim	1.00	0.42	1.00	0.42	1.00	0.42	1.00	0.42
	Err	0.1%	-3.5%	0.1%	-3.5%	0.1%	-2.4%	0.1%	-2.3%
	Est	0.99	0.55	1.00	0.55	0.99	0.54	1.00	0.54
10	Sim	1.00	0.54	1.00	0.54	1.00	0.54	1.00	0.54
	\mathbf{Err}	0.5%	-2.3%	0.4%	-2.4%	0.5%	-1.3%	0.5%	-1.4%
	Est	0.98	0.67	0.98	0.67	0.98	0.67	0.98	0.67
15	Sim	1.00	0.67	1.00	0.67	1.00	0.67	1.00	0.67
	\mathbf{Err}	1.8%	-0.5%	1.5%	-0.8%	1.9%	0.3%	1.6%	0.1%
	Est	0.94	0.80	0.95	0.80	0.94	0.79	0.95	0.79
20	Sim	0.98	0.81	0.98	0.81	0.98	0.81	0.98	0.81
	Err	4.2%	2.1%	3.4%	1.8%	4.3%	2.8%	3.5%	2.4%
	Est	0.86	0.90	0.87	0.90	0.86	0.89	0.87	0.90
25	Sim	0.91	0.93	0.91	0.93	0.91	0.93	0.91	0.93
	Err	5.5%	3.7%	4.4%	3.4%	5.7%	4.2%	4.7%	3.8%
	Est	0.75	0.96	0.75	0.96	0.74	0.96	0.75	0.96
30	Sim	0.78	0.99	0.78	0.99	0.78	0.99	0.78	0.99
	Err	4.4%	2.7%	3.6%	2.5%	4.6%	3.0%	3.9%	2.8%
	Est	0.62	0.99	0.62	0.99	0.62	0.99	0.62	0.99
35	Sim	0.64	1.00	0.64	1.00	0.64	1.00	0.64	1.00
	Err	2.6%	1.1%	2.4%	1.0%	2.9%	1.2%	2.7%	1.1%
	Est	0.50	1.00	0.50	1.00	0.50	1.00	0.50	1.00
40	Sim	0.51	1.00	0.51	1.00	0.51	1.00	0.51	1.00
	Err	1.7%	0.3%	1.7%	0.3%	1.9%	0.3%	1.9%	0.3%

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Multi-scale Transactive Control In Interconnected Bulk Power Systems Under High Renewable Energy Supply and High Demand Response Scenarios: Auxiliary Report

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Abstract

This document is an auxiliary report to the doctoral dissertation entitled "Multi-scale Transactive Control In Interconnected Bulk Power Systems Under High Renewable Energy Supply and High Demand Response Scenarios" by David Chassin, presented on November 15, 2017 at the University of Victoria in British Columbia, Canada [1].

1 System overview

This section presents an overview of power system operations, the role of demand response and a history of transactive control in electric power systems. When loads act as a resource situated in electric power systems, we are motivated to ask how demand resources can be used to provide needed services in electric system planning and operations, how the individual responses of consumer devices are aggregated to enable practical application of load as a resource, and what may be the environmental and emissions impacts of employing demand response control. These questions are very complex and difficult to answer in the context of today's fast-evolving electricity infrastructure. The changing nature of the system, the economic and regulatory context, and the loads themselves are all conditions that must be considered if we are to employ demand response to affect such as mitigating renewable intermittency, empowering consumers, and reducing the cost of system operation.

Responsibility for the reliability of electricity interconnections is shared by all the operating entities within each interconnection. In a traditional power system, these entities are vertically integrated. A committee process involving all the entities within each power pool establishes the reliability criteria utilities use for planning and operations. Typically, the operating entities belong to larger regional coordinating councils so that they can coordinate their criteria with neighboring power pools. Since 1965 these regional councils have been organized under what is now called the North America Electric Reliability Corporation (NERC), which establishes the standards for system reliability [2].

With the evolution toward market-based operations in recent decades, vertically integrated operating entities have been broken up into generation companies (GENCOs), transmission owners (TRANSCOs), load serving entities (LSEs), and energy traders that do not own assets, all of whom are collectively the market participants [3]. The responsibility for ensuring the reliability of a control area is delegated to independent system operators (ISO) or regional transmission operators (RTO). In general, market participants have the duty to provide accurate data about their assets and prices, as well as follow the dispatch orders of the ISO/RTO. The ISO/RTO has the duty to ensure that each market participant meets the reliability rules, and determines the dispatch orders necessary for the electricity supply and demand to match according to NERC's reliability standards. This system is predicated on a successful competitive market in which private decentralized trading and investment design work to allow substantial commercial freedom for buyers, sellers and various other types of traders [4].

The method used to implement such a system planning and operating model uses a two-stage process referred to as the "unbundled" or "twosettlement" approach:

1. Unit-commitment (UC) is a days-ahead process

that determines the hourly operating set points of the generation assets based on their bid energy prices and the forecast system load.

2. Economic-dispatch (ED) is an hours-ahead process that determines the real-time generation schedules and procures additional supply to ensure system reliability.

This two-step approach can be used for both regulated and unregulated markets and the analysis method is similar for both short-term operations and long-term planning with the only caveat that ISOs must perform the system studies for deregulated markets to determine whether additional generation and transmission may be required.

Overall the time frames for planning and operations can be separated into the following security functions [5]:

- 1. Long term planning (2-5 years) determines needed investments in generation and transmission.
- 2. Resource adequacy (3-6 months) secures generation to serve expected load and sets long-term maintenance schedules.
- 3. Operations planning (1-2 weeks) coordinates short-term maintenance schedules and longlead generation.
- 4. Day-ahead scheduling (12-24 hours) performs a security-constrained UC using energy bids.
- 5. Real-time commitment and dispatch (5-180 minutes) performs real-time security-based economic balancing of generation and load.

For time intervals shorter than about five minutes, the reliability of the system is delegated entirely to the generation and loads according to reliability standards promulgated by NERC and coordinated separately by each interconnection.

1.1 NERC Reliability Standards

The North American power system is divided into two major interconnections, Eastern, Western and three minor interconnections: Quebec, Texas and Alaska (in approximate order of total generation capacity). One or more reliability councils govern each interconnection. Six reliability councils govern the Eastern Interconnection: Florida (FRCC), Midwest (MRO), Northeast (NPCC), ReliabilityFirst (RFC), Southeast (SERC) and Southwest (SPP). The Western interconnection is governed by WECC, Texas is governed by ERCOT, Quebec is governed by NPCC, and Alaska by ASCC (which is a affiliate member of NERC) [6].

Each interconnection is operated as a single large machine. Each generator contributes in synchrony with every other generator to supply electric energy to the interconnections' customers. The angular velocity ω of the generators at steady state determines the system frequency $f = \omega/2\pi$. However, if the power generated differs from the power consumed, the frequency will change according to the swing equation $df/dt = M\Delta P + D\Delta f$, where M is the inertial constant of the interconnection, ΔP is power deviation, D is a system-specific frequency correction term, and Δf is the frequency deviation from nominal [7]. At steady state the frequency is the same throughout the entire interconnection.

Balancing Authorities (BA's), of which there are at present 131 in the United States, manage the balance of generation and load. Each BA dispatches generators to meet their individual needs, although some BA's also control loads. The BA's are connected via high-voltage transmission lines (called tie-lines) to neighboring BA's. If one BA has too little generating capacity to support its native load, it can schedule a transfer of power from other BA's with available generating capacity within the same interconnection. The ability to transfer power between BA's is the foundation of an interconnection's reliability.

Because the frequency is the same across all the BA's in an interconnection, each BA must consider two inputs to the control of generation (and load, if applicable):

- **Interchange error:** net flow balance of power relative to the scheduled transfer.
- **Frequency bias:** the obligation to provide energy to support frequency stability.

Each BA uses a common set of meters on the tielines connecting it to its neighbors to monitor and account for interchanges. Consequently all generators and loads fall strictly within the boundary of a metered region of balance control. However, only some of the generators within a particular BA are directly controlled by the BA to correct for interconnection frequency and scheduled tie-line flow deviations.

1.2 Balancing and Frequency Control

Customer demand and uncontrolled generator output vary continuously within each BA resulting in unintentional deviations from scheduled tie-line flows and interconnection frequency. Consequently, BA's must continually adjust controlled generator output by quantifying the mismatch in their interchange obligations as well as their frequency support obligations. This mismatch is estimated using the Area Control Error (ACE) in MW. Operators in each BA monitor ACE and dispatch generation resources (and sometimes load) to keep it within limits that are generally proportional to the size of the BA. The dispatch control is accomplished through a combination of automation, human and market (either bilateral or open) actions, and if necessary emergency actions such as automatic or manual generation or load shedding.

ACE is to a BA what frequency is to an interconnection: when ACE is high it indicates overgeneration in the BA and reflects upward pressure on the system frequency; when ACE is low it indicates under-generation in the BA and reflects downward pressure on the interconnection frequency. However, when ACE is the same sign as the frequency error, it tends to increase ACE and when frequency error is the opposite sign it tends to decrease ACE. This relationship is captured in the CPS-1 performance standard. Failure to maintain balance, as well as other grid problems such as congestion, equipment faults, and other rapid unilateral adjustments in generation or load will cause frequency variations that are reflected in violations of the CPS-1 standard.

BA control is maintained over a continuum of time ranging from seconds to hours and is divided accordingly into four levels of control:

Primary control: The primary frequency response that occurs within seconds of a disturbance in the frequency. It is provided by governor action on generators, which sense changes in the generators' speeds and adjusts the input to the generators' prime movers. It is also affected by certain loads such as motors whose speeds drop with frequency, by frequency protections that interrupt load at pre-defined frequency levels, and by firm load curtailment programs that ensure stability under severe disturbance scenarios.

Because generator loss is the most common system disturbance, the amount of Spinning Reserve in the interconnection determines the available frequency response. It is understood that a) primary control does not restore frequency, it only arrests the frequency excursion, and b) operators must continually monitor their frequency response resources to ensure that Blackstart Units are able to control frequency and arrest excursions.

Secondary control: Balancing services are controlled in the "minutes" timeframe (although some resources can respond faster; e.g., load and hydroelectric units) using the BA's' AGC system and supplemented with manual actions by the dispatchers. AGC computes the ACE and determines the most economical way for the available resources to restore balance, and sends set points to the affected generators (and loads, if any).

Initial reserve deployments after a disturbance can also be initiated under secondary control. These resources maintain the minute-tominute balance needed to restore frequency to its scheduled value following a disturbance and are usually drawn from both Spinning and Non-Spinning Reserves.

- **Tertiary control:** These are the actions taken to set reserve resources in states that allow operators to handle current and future contingencies. This is particularly important after a disturbance, when new reserves must deployed or restored.
- **Time control:** Although frequency and balance control is very accurate, it is not perfect and errors due to transducer inaccuracies, problems with the SCADA hardware or software, or communications errors can lead to integral errors in frequency that must be corrected over the long term. The Time Monitor compares a clock driven by the interconnection frequency to an official reference time at NIST. In most

interconnections the Scheduled Frequency is changed when the Time Error exceeds a certain threshold. In WECC a Time Error Correction (TEC) is applied automatically through the Automatic Time Error Correction software.

Table 1 enumerates the services provided, the time horizons over which they are relevant and the NERC standard that governs the adequacy of the service.

1.3 ACE Calculation

The area control error signal is called ACE and is calculated by each BA using the following equation

$$ACE = (P_a - P_s) - 10B(f_a - f_s) - E_m$$

where P_a is the actual net interchange (in MW), P_s is the scheduled net interchange (in MW), B is the BA's bias (in MW/dHz), f_a is the actual frequency (in Hz), f_s is the scheduled frequency (which may be offset ± 0.02 Hz when TEC is active), and E_m is an measurement error correction factor to address inaccuracies that arise when using instantaneous flow measurements as hourly meters on tie-lines [2].

The actual power and frequency measurements are provided by each BA's SCADA system approximately every 4 seconds although timesynchronization of the measurements is not guaranteed [7].

1.4 Ancillary Service Markets

Market designers identify system operators as the party responsible for reliability in a way that is compatible with competitive energy markets. One of the key lessons learned from California's market failure is that the definition of what constitutes an ancillary service is critical to ensuring sufficient liquidity, which influences reliability. A key aspect of the ancillary service market designs coming out of the 1990s is the recognition of cascading downward substitutability of reserve resources because faster responding resources are considered higher quality [8]. Consequently price inversions (viz., slower reserves getting higher prices) are an undesirable property of ancillary service markets and can lead to perverse incentives and inappropriate bidding. Unfortunately early solutions to market design problems varied and appeared to address ISO-specific concerns rather than the broader issue of what constitutes a "good" reserves market design.

Reserve markets can be viewed as a multi-part auction where resources compete to provide reserve services by submitting two bids, one for capacity and one for energy. The resource ranking is determined by the capacity price and pays all bidders the price of the last capacity resource reserved. The energy bids are only used when the reserves are called, and then all called reserves are paid the highest energy price of the reserves called. Such a market design was proven to be incentive compatible, meaning that bidders are induced to reveal their true marginal energy and capacity costs [9].

1.5 Current US Market Designs

In 2012 the US Department of Energy commissioned a survey of how the seven major ISOs and RTOs operate their reserve markets [10]. In general these ISO/RTO's require the entities that serve loads to provide reserves in proportion to their loads. However, most of these entities do not have generation resources of their own, so they must acquire reserves through bilateral contracts or through centrally organized open markets where they exist. To date, seven such markets have been organized in the US: CAISO, ERCOT, ISO-NE, MISO, NYISO, PJM, and SPP.

None of these markets provide for trading of primary frequency control or time control. Only secondary and tertiary control reserves are traded in open markets. Each of the ISO/RTOs defines which reserves can be traded in open markets slightly differently. In addition, markets often use different terms to describe similar resources and in some cases the same term can refer to different services. This has led to considerable confusion about what, when and where ancillary services can be provided in markets. Table 2 summarizes the different terms used for various secondary and tertiary control reserves. Each market has individual characteristics that distinguish it from others. These are summarized in Table 3.

The procurement of services in all seven ISO/R-TOs is completed following a co-optimization of energy and reserve resources. The specific cooptimization methods used differ; some are integrated, some are coupled, and some are decou-

Control	Service	Timeframe	NERC Standards	
Primary Control	Frequency Response	10-60 Seconds	FRS, CPS1	
Secondary Control	Regulation Reserves	1-10 Minutes	CPS1, CPS2,	
			DCS, BAAL	
Tertiary Control	Imbalance Reserves	10 Minutes-Hours	BAAL, DCS	
Time Control	Time Error Correction	Hours	TEC	

 Table 1: Control continuum summary

Table 2: Reserve market terminology in the US

Market	Secondary	Tertiary	Other reserves
CAISO	Reg Reserve: ⁽¹⁾ • Reg up • Reg down	Spinning Reserve	Non-spinning Reserve
ERCOT	Reg Svc: ⁽¹⁾ • Reg up • Reg down	Replacement Reserve Svc	Non-spinning Reserve Svc Replacement Reserve Svc
ISO-NE		10-min Spinning	10-min Non-Spinning 30-min Non-Spinning
MISO	Reg Reserve	 Contingency Reserve: ⁽¹⁾ Spinning Reserve 	Supplemental Reserve
NYISO		10-min Spin Reserve	10-min Non-sync Reserve 30-min Spinning Reserve 30-min Non-sync Reserve
PJM		Contingency Reserve: ⁽¹⁾ • Sync Reserve	Quick Start Reserve Supplemental Reserve
SPP ⁽²⁾	Regulation: ⁽¹⁾ • Reg up • Reg down	Contingency Reserve: ⁽¹⁾ • Spin Reserve	Supplemental Reserve

Source: Ellison (2012).

Notes:

⁽¹⁾ Categories of reserve markets.

⁽²⁾ SPP information is based on their proposed market design.

pled co-optimizations. PJM's co-optimization is coupled in forward markets with continuous realtime adjustments. ISO-NE supports a decoupled co-optimization in forward markets with a coupled real-time market. ERCOT supports integrated cooptimization in day-ahead markets and coupled in real-time. MISO, NYISO and CAISO support fully integrated co-optimization of energy and reserve resource markets.

The settlement practices of the ISO/RTOs have come under considerable scrutiny from FERC. As of 2014 only ISO-NE and NYISO had any form of payfor-performance. The remaining five ISOs pay only for the capacity accepted by the market. This was the motivation for FERC Order 755, which requires compensation for regulation based on actual services provided [11]. The impact of this order has yet to be realized in new settlement policies that conform to its intent.

Finally, FERC Order 745 addresses how demand response is compensated in wholesale energy markets (rather than reserve markets). This order requires that dispatch of demand response be subject to a net-benefits test to determine whether it is costeffective, and when it is dispatched that it be compensated at the market price for energy (e.g., the lo-

	Product Characteristics ⁽¹⁾	CAISO	ERCOT	ISO-NE	OSIM	OSIYN	PJM	$\mathrm{SPP}^{(2)}$
	Regulation Reserves (secondary frequency control)							
	• Governor control required?	No	\mathbf{Yes}	N_{O}	Yes	N_{O}	N_{O}	N_{O}
	• Separate up/down regulation markets	\mathbf{Yes}	${ m Yes}$	N_{O}	N_{O}	N_{O}	No	\mathbf{Yes}
	• AGC signal required?	\mathbf{Yes}	$\mathbf{Y}_{\mathbf{es}}$	\mathbf{Yes}	Yes	$\mathbf{Y}_{\mathbf{es}}$	Yes	\mathbf{Yes}
	• Maximum time to deliver called capacity	10-30	10	ഹ	ъ	ഹ	ъ	
	• Minimum duration to sustain called capacity	(3)		09	60			60
	• Minimum ramp rate (MW/m)			1				
	• Minimum capacity offered		$1 \ \mathrm{MW}$				$0.1 \ \mathrm{MW}$	
	Spinning Reserves (tertiary frequency control)							
	• Governor control required?	No	$\mathbf{Y}_{\mathbf{es}}$	N_{O}	No	N_{O}	N_{O}	N_{O}
	• Maximum time to deliver called capacity	10	10	10	10	10	10	10
19^{-1}	• Minimum duration to sustain called capacity	30		09	00			00
1	• Minimum capacity offered		$1 \ \mathrm{MW}$					
	• Two-tiered market?	No	No	N_{O}	No	N_{O}	Yes	No
	Non-Spinning Reserves							
	• Maximum time to synchronize at called capacity	10	30	10	10	10	10	10
	• Minimum duration to sustain called capacity	30		09	60			00
	• Minimum capacity offered		$1 \ \mathrm{MW}$					
	Supplemental Reserves							
	• Synchronized and non-synchronized markets split	N/A	N_{O}	N_{O}	N/A	Y_{es}	N_{O}	N/A
	• Maximum time to synchronize at called capacity	N/A	Contract	30	N/A	30	30	N/A
	• Minimum duration to system called capacity	N/A	Contract		N/A			N/A
	Source: Ellison et al. (2012).							
	Notes:							
	(1) All units are minutes unless otherwise noted.							
	⁽²⁾ SPP information is based on their proposed market design. ⁽³⁾ Values can be anywhere in this range.							
	2							

Table 3: Characteristics of US electricity reserve market

cational marginal price) [12]. The order's objective is to remove barriers to participation for demand response, but it has been criticized for not recognizing the nature of demand in organized electricity markets [14]. For example, the value of the LSE's obligation to serve is not reflected properly in the demand curve, and therefore a demand "negawatts" should not be priced as supply "megawatts". Such issues have yet to be properly addressed by regulators, market designers, market operators, load serving entities, and regulation service providers.

1.6 Ancillary Services Using Demand Resources

Modern bulk electric interconnections are constrained by the physical requirement that electric energy is not stored in any substantial way during system operations. Historically, utility operations have focused on controlling generation to "follow" load to ensure that at every moment supply exactly matches demand and losses. To make electric utility planning and operation economical and manageable, the industry divides generation resources into three principal categories: base load, intermediate load, and peak load [7].

Base-load generation is the bottom portion of the supply stack that essentially runs uninterrupted throughout the year (except during maintenance or unplanned outages). Intermediate-load generation runs continuously but only seasonally as the diurnal load nadir rises and falls. Peak-load generation is the supply that must be started and stopped daily to follow the diurnal load variations. Each of these types of generation also provides regulation and reliability resources to help control frequency and respond to contingencies and emergencies in generation and transmission operations.

For decades, load had not generally been considered part of the overall planning and operations model of electric interconnections except to the extent that its growth sets the conditions for capacity planning. But in recent years increasing thought has been given to the role that load can play as a demand resource that a) reduces the need for new conventional generation resources, b) avoids using generation resources in inefficient ways, and c) enables the addition of generation resources that exhibit substandard performance characteristics when operating under the conventional load fol-

lowing paradigm [13].

Today the term "demand resource" encompasses a wide range of products, services, and capabilities related to the control and management of load in electric systems. Prior to the advent of "smart grid" technology, demand resources were primarily considered for planning purposes, such as demandside management (DSM) programs, and very limited operational purposes such as in extremis underfrequency or under-voltage load shedding programs (UFLS/UVLS). DSM programs focus on energy efficiency and other long-term demand management strategies to reduce load growth so that the need for significant new generation capacity investments can be reduced or deferred. Generally these programs pay for themselves by reducing capital costs for a number of years, possibly indefinitely. DSM programs helped the industry transition from its pre-1970s 7% annual capacity growth to the sub-3% growth prevalent today in modern electricity interconnections.

This section reviews some of the recent trends and the developments in demand response as a resource and how it can address a wider range of operational and economic system needs. The focus is particularly on the limitations of advanced demand response programs and the ongoing research to address these challenges.

1.6.1 Load as a Resource

Demand response programs have generally been divided into two major categories: incentive-based programs and price-based programs. Both categories recognize that there is an essential economic component to developing demand response capabilities in electric systems, but realize the economic benefits in very different ways. As a general rule, incentive programs are contractual, typically bilateral arrangements between customers and system operators to provide direct load control, interruptible load, or market-based control strategies for emergency reserves and ancillary services. In contrast, price-based programs use utility rate structures and energy prices such as time-of-use rates, critical-peak pricing, or real-time pricing to drive demand to be responsive to system conditions through economic signals as a proxy for direct control signals [14].

However, the ability of load to provide resources that serve system planning needs such as capacity investment deferrals or operational needs such as ancillary services is limited by (1) the intrinsic nature of the devices and equipment composing enduse loads and the constraints arising from consumer behavior and expectations, (2) our ability to control the loads in an appropriate and dependable manner, and (3) our ability to validate, verify, and meter their contributions to system planning and operation.

1.6.2 Load Modeling

The electric utility industry is extremely risk-averse because such a high value is placed on system reliability. As a result, new technology is often limited by the ability of planners to simulate its effect in the planning studies used to establish system operating limits, and by the ability of operators to control these technologies in real-time. In both cases, the challenge is not only modeling the technology itself, but also, more critically, simulating how the technology interacts with the bulk power system. In the case of loads as resources for system planning and operation this modeling issue centers on three fundamental questions: (1) How do electric loads behave at various times of day, week, year? (2) How does end-use composition evolve over these time frames? And (3) how does the control of loads affect these behaviors in shorter time horizons?

Load behavior is determined by both the electromechanical properties of the devices and equipment connected to the electric system and by the behavior of the consumers of the services they provide. As a general rule utilities categorize loads by enduse, such as cooling, heating, refrigeration, lighting, cooking, plugs, washing, and drying in the residential sector. In commercial buildings other enduses such as computing, process pumping, conveying, and other services are also considered. Daily, weekly, and seasonal load-shapes are associated with each of these end-uses to provide analysts with an empirical data set from which to estimate load under different conditions. Load shapes have the advantage of capturing in a single data set both the electro-mechanical behavior and the consumer behavior that gives rise to the overall shape of loads [15].

However, these load shapes have a serious drawback when one attempts to determine the degree to which a load changes in response to a short-term signals such as dispatch commands, real-time prices, frequency or voltage fluctuations: load shapes contain no information about the inter-temporal correlation of the loads' energy, power and ramping behavior. Devising load models that incorporate these remains an ongoing area of research and tools such as LOADSYN [16], the WECC Composite Load Model [17], and GridLAB-D [18] partly address this problem.

Load composition models were developed to address a problem that generally does not arise when considering load behavior over hours or more. Each load is composed of electrical subcomponents that have independently changing sub-hourly electromechanical characteristics. Induction motors of different types, sizes, and control may start and stop; electronic power drives may be used; and the overall mix of static power, current, and impedance may change very quickly in response to dynamic frequency/voltage events, economic or dispatch signals, whether due to the normal internal control behavior or equipment protection subsystems. Although the overall energy consumption on the hourly time scale may be described well using load shape data, the sub-hourly dynamics of power demand may be quite volatile and are often poorly understood. This lack of understanding can present system planners and operators with challenges for which few tools exist, as has been observed in the case of fault-induced delayed voltage recovery [19].

Load diversity is an emerging challenge when external control signals are applied to devices and equipment. Under normal operating conditions, loads that cycle on and off are assumed to have high diversity, meaning that their cycles are relatively independent of bulk system conditions. The difficulty is that diversity is a property of loads similar to entropy; it is difficult to directly observe and it can only be considered when compared to a reference state, such as the equilibrium state of a class of loads. Conventional models of loads assume the diversity is maximal (at equilibrium). But in practice, load control strategies reduce diversity, sometimes to a significant degree. In spite of these challenges, models that indirectly consider the entropy of certain load classes have been developed and applied to load control problems with some success [20, 21, 22]. But a comprehensive and theoretically sound model for diversity continues to elude load modelers, and this remains an open area of research.

Human behavior is a critical consideration when designing load control programs. Utilities must consider two distinct aspects of human behavior to determine the viability and success of a load control program. The first is customer recruiting and retention (the customer pays for electric services but may not be the same person as the consumer who uses the end-use service), and the second is real-time consumer participation. Customer expectations are set during the recruiting phase when utilities make a cost-benefit case for customers to opt into demand response programs. (Demand response program marketing is primarily economic in nature but often includes an environmental component.) After customer acquiescence, technology is usually deployed in the customers' facilities and consumers are presented with behavioral choices by the technology. The frequency of these choices can range from daily (e.g., postponing a load of laundry) to seasonal (e.g., resetting a thermostat). Expecting consumers to make choices more than once a day for any particular end-use is generally regarded as impractical and it is also usually ineffective to ask consumers to make choices less frequently than seasonally [28]. Mitigating consumer fatigue and providing continuous education have also been observed to be factors in ensuring that demand response programs are cost-effective and sustainable [29] [30]. Finally, utilities frequently face fairness and "free-rider" questions when customers sign-up for programs but provide no value to the utilities because either a) customers already exhibit the behavior sought, or b) the utility never calls on them to exhibit the desired behavior [31]. Ultimately the long-term effectiveness of demand response programs and the technologies that support them hinges on whether the customer benefits outweigh the consumer impacts. If there is any disconnect between customers/consumer short-term/longterm value/impacts, they will not remain in the program long enough for the program to pay for itself, let alone provide the anticipated system benefits to the utilities and system operators [32].

Until the advent of utility deregulation, demand response programs were the exclusive purview of utilities and regulated accordingly. However, in regions where vertical integration has been overcome, third-party aggregation has become a viable business model for providing demand response from many smaller customers as a single homogenous capability that is easier for a utility or an ISO to interact with. By using on-site control technology, utility service contracts, and rebate programs, aggregators can create both arbitrage and value-added opportunities from which to generate sufficient revenue. In some cases, monopsony/monopoly conditions can emerge as a result of regulatory intervention, technology locked-in high front-end equipment costs and high back-end system integration costs [33]. A recent additional concern is that demand response aggregation is potentially subject to FERC jurisdiction to the extent that aggregators acquire and deliver resources across FERC jurisdictional boundaries or interact with ISO and RTO entities subject to FERC oversight. Indeed, FERC has recently issued orders affecting how demand response is compensated in energy markets, which raises the question of whether and how it might intervene regarding demand response compensation in ancillary service markets [34].

Finally, load models ultimately are embodied in the simulation tools utilities use in planning studies and operational analysis, such as forecasting models and even billing systems where baseline load models are part of the contract. New load models can take a very long time to be adopted by industry and become commercially available in planning and operations products. For example, the Western Electricity Coordinating Council's Load Modeling Task Force began developing a new load model in 2001 but it was not adopted until the Summer 2013 cases. In the interim a flat 20% induction motor load was used after it became apparent that the standard load model was in part responsible for the discrepancies observed in the August 1996 outage studies [35]. Such delays can significantly reduce the impact and potential benefits of load control technology and approaches to faster load model adoption are still needed.

1.6.3 Load Control

Demand response as a tool for providing ancillary services relies on the ability to control aggregate loads. The time scales over which loads can respond to dispatch signals, and the return to "ready" state determine the frequency and magnitude of load response as it performs desired ancillary services. The models for load control (as opposed to load behavior) have yet to be developed. Work to describe the frequency and amplitude response of modern loads and load controls has only recently been undertaken, and significant research remains to be done in this area [36].

A fast emerging obstacle to effective deployment of large-scale load control systems is the lack of a comprehensive theory of control for distributed systems. Understanding how we regulate devices and systems in our environment is a prerequisite for managing those devices and systems. That understanding is captured in control theory, the body of formalisms that explain how we observe, control and verify key performance characteristics of engineered systems. The challenge today is that although controllability and observability are welldefined for simple systems through the Kalman rank condition, and stability can be studied using methods named after such as Ziegler, Nichols, Bode, Nyquist, and others, the emergent behavior of interconnected systems has yet to be considered formally. As a result, ad hoc models of robustness, security, and stochastic behavior have been overlayed on conventional control theory. Physical constraints are often ignored, information flow is assumed instantaneous, and evolving network topologies are not well treated, so that only trivial problems are solved [37].

The paradigm for larger, more complex and realistic systems continues to elude system engineers. We have yet to understand complex engineered systems well enough to design and control them, let alone exploit the new behaviors and possibilities inherent when linking previously independent systems into a more heterogeneous multi-technical complex of systems. In short, we need a new approach to controlling the large interconnected multi-technical complex that is emerging. The new approach must allow systems to adapt and evolve without individual components being redesigned, retested, and redeployed every time relevant parameters change. Simply put, a new paradigm of control is needed for complex systems.

1.6.4 Validation, Verification and Metering

Using demand response as a resource for planning and operation depends on our ability to ensure that the tools we use for bulk power system control are accurate, work as designed for all conditions (both foreseeable and unforeseeable) and that we can monitor and meter the performance of these resources for both operational and business objectives.

Model and simulation validation for very complex models such as the load models currently in use is a daunting challenge in itself. Empirical end-use and load composition data collected by utilities degrade quickly and unpredictably as end-use technologies change, efficiency standards take hold and consumer habits evolve. Although utilities know that consumer assessment surveys are essential to maintaining accurate load models, the cost of conducting these surveys has been historically prohibitive. Many utilities and advocates of automated meter reading technology frequently cite improved consumer behavior data as one of the principal longterm benefits of automatic metering infrastructure. However, these benefits have yet to be demonstrated in practice, particularly as data privacy and security concerns begin to emerge [38].

Tool validation presents additional challenges, particularly when tools become multi-disciplinary and rely on hybrid numerical methods, such as agent-based solvers. Although these analysis tools are highly realistic, they rarely have a reference model or baseline data to compare against. As a result, confidence in these tools builds more slowly and the rate of adoption of advanced simulations is slower than has historically been true from more conventional power system analysis tools [39].

Control system verification remains an open research area for distributed control systems such as the large-scale demand response systems being designed and tested today. Utilities historically relied on strictly hierarchical direct load control programs that used isolated and simple control structures and were easy to verify. Systems that rely on autonomous responses or price signals are more likely to exhibit stochastic behavior that raise concerns regarding their reliability under extreme events, when they may become critical to system integrity [40].

Monitoring and metering are closely related to the question of verification and present additional challenges. Utilities must measure how much resource is available in real-time to ensure that sufficient resources are deployed to provide the required contingency response. So-called "transactive control" systems have the notable advantage that they provide resource availability data concurrently with the required resource cost data. Finally, when events occur, utilities also need to measure which resources were actually deployed before compensating customers for their participation. To date the designs of advanced demand response systems have largely failed to satisfactorily address either of these issues [41].

1.7 Demand Response Aggregation Strategies

In the previous sections, the role of ancillary services and the potential for demand response to provide such services were discussed in detail. As intermittent generation becomes a standard element of the generation fleet, the interest in using demand response as a substitute for new controllable generation is expected to grow. In addition, demand response has long been regarded as necessary because it reveals the elasticity of demand in a way that mitigates supply-side market power.

One of the most significant obstacles to using demand response to simultaneously displace generation-centric reliability services and mitigating generator market power is the mismatch in the characteristic size, time, and uncertainty of loads relative to generators: there are relatively few easily observed generators and their characteristic response times are relatively slow compared to overall system dynamics. Loads in contrast are far smaller, far more numerous and difficult to observe, but potentially far faster acting that the overall system dynamics [42].

Bulk power system planning, operation and control have generally been designed to consider the characteristics of generators and treated loads as a "noisy" boundary condition. Thus load control remains quite difficult to incorporate into bulk system planning and operation. In general, the approach to addressing this fundamental mismatch is to devise demand aggregation strategies that collect numerous small fast acting devices with high individual uncertainty into a few large slower acting aggregations with reduced uncertainty. While not requiring every electric customer to participate in wholesale markets, demand aggregation provides a means of increasing consumer participation in system resource allocation strategies—market-based or centrally controlled—and thus can mitigate the price of energy, capacity, or ramping services [43].

From an economic perspective, aggregating electricity customers can be viewed as a means of capturing consumer surplus to increase producer sur-

plus by segregating consumers into groups with different willingness to pay. Three general approaches are usually employed to creating consumer aggregation for either operational or economic objectives:

- 1. Economic aggregation is achieved using price discrimination methods such as different rates for different customer classes, product differentiation, and product or service bundling strategies.
- 2. Social aggregation is achieved using various subsidy programs, and other social group identification strategies such as environmental, green or early-adopter programs.
- 3. Technical aggregation creates technical structures that either directly aggregate consumers or indirectly enable economic or social aggregation. Technical aggregation can be accomplished using service aggregators, creating technological lock-in with high barriers to entry or exit, or constructing local retail markets independent of wholesale energy, capacity, and ancillary service markets.

This section discusses the motives, principles and practices generally employed by the electric power industry in achieving consumer (and demand response) aggregation.

1.7.1 Economic Aggregation

Price discrimination is an economic strategy used by sellers to capture additional consumer surplus. Surplus is the economic benefit derived by bringing buyer and seller together to trade electricity products and services. As long as the consumer's reservation price exceeds the producer's they are both overall better off economically if they complete the trade. The net difference between the consumers' economic welfare with electric and their welfare without electricity is defined as the consumer surplus. Similarly, the net economic benefit to electricity producers between producing electricity and not producing electricity is defined as the producer surplus. It is the objective of both consumers and producers to maximize their respective surpluses, which in an efficient market results in the total surplus being maximized as well [44].

However producers recognize the some consumers have a greater willingness to pay for products and services. Consequently, producers can devise pricing strategies that divide the consumers in a way that increases their surplus but does not increase the total surplus, instead capturing some of the consumers' surplus. The most common of these is to create different rate structures for each customer sector (e.g., residential, commercial, industrial, mu-In theory such strategies nicipal, agricultural). have been shown to maximize producer surplus only when the demand curve is strictly convex toward the origin, but in practice this limitation is often ignored. Even though it may seem unfair to consummers that some pay less for the same product or service, price discrimination is regarded as a standard practice justified by the cost recovery needs of a capital intensive industry, and such practices are regularly endorsed by electric utility regulators [45].

Volume discounts are another common form of price discrimination that serve to aggregate consumer behavior. In the case of electric utilities, the most common form is the declining block rate, which recognizes that customers with a higher demand also have a more predictable peak demand than smaller customers. The cost of operating electric power systems is driven in large measure by the cost of serving unpredictable peaks, so more predictable customers are offered discounted rates for the "good" behavior. In effect these customers are consuming a lower quality product: one that does not need to vary as much relative to the total and therefore costs less to produce. An unfortunate side effect of declining block rates is that they can be a disincentive to conservation and many utilities are moving away from such rate structures. Increasing block rates do promote conservation but this approach requires very careful analysis to predict the seasonal peak load variations. When significant numbers of customers come under such a rate, utility revenues can become much more sensitive to weather fluctuations than they already are [46].

Very likely the most well known form of price discrimination employed by utilities is product differentiation, viz., charging residential customers for energy usage and commercial/industrial customers for power capacity. This form of customer aggregation recognizes that residential and small commercial customer behavior (e.g., individual appliance and equipment purchases) is more closely correlated with energy consumption and large commercial/industrial/agricultural customer behavior (e.g.,

increasing production capacity) is more closely correlated to peak power demand. Utilities seek to have behavior and bills as strongly correlated as possible, and therefore prefer energy rates for residential and small commercial customers and power or demand ratchet rates for large commercial, industrial and agricultural customers [47].

The final form of economic customer aggregation, service bundling, is the most ubiquitous in electricity delivery. The historically regulated nature of the utility business means that product bundling isn't thought of as a business strategy to increase revenues per se (as in the telecommunications business). Instead the capital-intensive nature of the business combined with the desire for simple billing (unlike the telecommunications industry) means that energy or power rates must include capital costs. Service bundling is considered as an appropriate net revenue volatility risk mitigation strategy, and regulated as such. Most customers pay for only one product composed of several underlying services; e.g., energy (with capacity and reliability) or capacity (with energy and reliability). All the underlying services that utilities provide, such as fuel price volatility hedging, capital financing, administration, and maintenance are blended into the simple price that each customer pays. There is some discussion of utility business models that unbundle these services to achieve more economically efficient operations by revealing the customers' different demand elasticities and reservation prices for each service. Utilities would then be able to serve customers with differentiated reliability services, for example. Most likely the technical and regulatory obstacles to this model are why it has not gained much more than academic interest. Perhaps we can expect growing interest in areas where distribution reliability is a significant issue for some customers or technical solutions like microgrids are prevalent. But that has yet to be adequately researched at this point.

1.7.2 Social Aggregation

Social aggregation is based more on human behavior than economic theory and is consequently less well understood. Utilities typically base their social customer aggregates on four types of social differentiators: income class, behavioral cross-subsidies, environmental awareness and early adopters. In many areas, utilities and governments provide subsidized service to low/fixed-income customers in the form of rebates, small customer rates, and special assistance programs. The reasoning is that electricity is considered an essential service in modern society that low/fixed-income customers cannot do without. Regulators generally view low/fixed-income customer subsidies favorably, especially in communities where large numbers of such residents live. So where subsidies are not taxpayer-funded they are commonly found with investor-owner utilities and municipals. They may be less common with public utilities and cooperatives, but evidence appears to be somewhat anecdotal at this point.

Cross subsidies based on primary consumption drivers (e.g., energy vs. capacity) are an unavoidable feature of electricity services because of the strong motivation utilities have to maintain a simple blended rate for each customer class. As a result of the design of the rates, one customer class is often effectively subsidizing another customer class, e.g., commercial customers subsidize residential or viceversa. Environmental/green products are a recent addition to the portfolio of social aggregations that utilities may use. Under these programs, customers are offered the opportunity to pay a premium for their power if the utility purchases renewable energy to serve the demand. Ironically, often the marginal energy cost for resources is very near zero while the capital costs may be subsidized by tax incentives to the merchant generators. Regardless, these programs represent a clear case of price discrimination based on the customer's socially-motivated willingness to pay more for a higher quality product.

Early adopter programs are another form of social aggregation that provides utilities the opportunity to test new products and services before making them available to mainstream customers. Early adopter customers are willing to pay for a product whose quality is more uncertain in the sense that it may be better than existing products but it also might not work as intended by the utility or expected by the customer.

In all cases social aggregation strategies help utilities manage customer perceptions and expectations while continuing to meet basic business objectives such as customer satisfaction, regulatory compliance, environmental goals and research and development obligations that help the utilities adapt and adjust to changing business and technical conditions.

1.7.3 Technical Aggregation

Technical customer aggregation strategies are less common in the electric utility business than might be expected for such a technology-intensive industry. Only a few types of technical customer aggregation strategies can be readily discerned in modern utilities operations. Most notable are direct and indirect load control, service aggregators, retail markets, and technology lock-in strategies.

Direct load control is the oldest and most established mechanism used by utilities to aggregate customer demand response and make customer behavior "work" for the utility. Although the guid pro quo is evident and real for direct load control programs, they are not as common as one might expect because the technical solutions tend to be rather intrusive and expensive to deploy. Typical examples include water-heater and air-conditioning curtailment programs where load control switches are installed on customer equipment to allow the utility to directly turn off load if needed. Customers are offered a rebate either for participation in the program (a reservation price) or for each event (a call price). The advantage of reservation pricing is that measurement of individual responses to events is not required to properly compensate customers who participate. Unfortunately, free-rider behavior is quite prevalent under reservation pricing, particularly if the resource is rarely called. Call pricing is more challenging because it requires measurement and verification of each individual customer response to determine compensation. In addition, for many types of loads it can be difficult to determine what the customer would have done had the load control signal not be sent, especially if calls are frequent or continual. Hence it is more difficult to determine the appropriate compensation for each call.

Indirect load control circumvents many of these issues by avoiding direct signals to individual customers in favor of a common signal sent to all customers who have agreed to participate in the load control program. Under such situations, reservation pricing is strongly favored, although event/call pricing remains a viable option. The primary advantage of indirect load control strategies is that they do not require the utility to determine individual signals to send to each customer. A single price or index signal can be sent to all customers in the program and control action in response to the signal is left to the customer, based on either economically rational expectations or contractual obligations. The challenge for utilities is to determine the precise value of the price or index signal needed to achieve a desired level of demand response. This problem can be addressed by the next two strategies.

Service aggregators are probably the most common technical customer aggregation strategy employed by utilities. Service aggregators are independent third-party entities that receive a dispatch objective (e.g., an index) from their utility customer and determine how to dispatch the participants they recruited to meet the utility's objective. The service aggregators are paid by the utility for their ability to meet the utility's objective, and part of the revenue from the utility is shared with the participants either in the form of added energy management and control equipment that can help reduce the participant's overall energy costs or in the form of an event/call rebate.

Retail capacity markets address the challenges of indirect load control using pricing signals. The advantage of retail capacity markets is that they provide price transparency and technology neutrality. Aside from violating some important assumptions regarding load duration and generation screening curves used in planning capacity expansion [49], the main disadvantage is that they require significant infrastructure investments both in the customer premises as well as the utility back-office systems. Retail capacity markets can also present utilities with the same capacity expansion dilemma facing transmission system operators: In the event a distribution system constraint causes prices to rise without a corresponding rise in production cost, the utility as the market maker collects a share of the surplus which it presumably uses to finance capacity expansion [50]. However, this scarcity rent is collected only from customers on constrained feeders and not from customers on unconstrained feeders. This goes against the fundamental tenet that the electric transmission and distribution system infrastructure itself is a public good, access to which should be priced uniformly. Ironically, any remedy to reinstate the basic nature of the public good would undermine the very demand response behavior that real-prices offer to elicit.

The final and perhaps most insidious technical strategy for customer aggregation is technology lock-in and high barriers to entry. Although in the rational economic model the cost of the technology previously procured by a customer should be viewed as a sunk cost, customers often remain with the technology they have in spite of the existence of an objectively less costly choice going forward. This often leads to persistent conditions where inferior technologies remain extant and causes significantly higher welfare losses than in more innovative industries [51]. Technology lock-in is often an explicit business strategy for technology and service providers to ensure that they capture a disproportionate share of the producer surplus long after more competitive technology is available. However, in the electric power industry the process is implicit in the capital-intensive nature of the business. That is in part the argument in favor of government-subsidized investments and technology transfer incentives in utility technology overhauls, such as for the nuclear technology in the late 1960s or renewable generation and automated metering in the late 2000s.

In the end, technical customer aggregation strategies usually support the economic, social, and business objectives of utilities and the government oversight that protects the public good portions of their operations. Technical customer aggregation is rarely an objective in itself but for various practical reasons research into technical aggregation is often divorced from these objectives. Indeed some aggregation technologies are criticized for not recognizing these considerations and falling far short of expectations given the costs [52].

The need for utilities to aggregate customers is enduring and the methods they use vary greatly. Utilities can employ economic and social aggregation methods to establish a robust and engaged base of customers with a greater willingness to provide demand response services. These services can be employed in electric power systems operations for energy conservation, peak load reduction and reliability services.

Although many of these aggregation methods have existed for decades, recent technological advances have enabled some of them to be revisited and enhanced. In particular, early adopter strategies offer utilities the opportunity to test new technologies to meet regulated research program investment obligations and avoid the risk of significant capital investments, while operators and customers have to opportunity to learn how to maximize the benefits of the programs before the committing to full-scale deployment.

Price-based strategies provide a balance of economic efficiency and risk mitigation by allowing utilities to transfer many of the costs more explicitly to customers and reducing the need to engage in pricevolatility hedging on their behalf through opaque rate design processes. But regulators remain wary of price-based aggregation strategies until they can be shown to be cost-effective and fair to all customers.

1.8 Environmental Impacts of Demand Response

In the previous sections, the role of ancillary services, the potential for demand response to provide such services and the strategies available to aggregate demand response services were discussed in detail. We found that (1) ancillary services provide a critical capability for interconnection reliability; (2) demand response has the potential to provide such services; and (3) demand response resource aggregation is necessary to integrate such capabilities into interconnection planning and operations. Variable (often called intermittent) generation is a growing fraction of the resource base for bulk power systems. The variable character of certain renewable resources in particular is thought to undermine the overall reliability of the system insofar as forecasts of wind and solar generation output have greater uncertainty than more conventional fossil, nuclear or hydroelectric generation resources. As a result, the expectation is that while variable renewable generation resources do displace the energy production capacity of fossil power plants, they may not displace as much of the power or ramping capacity of those plants. Consequently, by their variable nature, renewable resources may indicate that they do not offer as much emissions benefit as expected if one were to assess their impact simply on energy production capacity [53].

It seems intuitive that demand response should be able to mitigate the capacity and ramping impacts of variable generation by reducing the need to build and commit fossil generation to substitute for reserves or ramp in place of fast-changing renewable generation. But this substitutability is constrained by (1) the nature of variable generation, the role of forecasting, and the impact of resource variability on the emissions and economics of renewable resources; (2) the nature of load variability and how demand response is related load variability; and (3) the characteristics of end-use demand and the impact of demand response on energy consumption, peak power and ramping rates over the various time horizons that are relevant to the variable generation question.

Taken together, these constraints and interactions provide the basis for assessing the economic and environmental impacts of controllable load and demand response resources on various time scales. It is by virtue of the downward substitutability of reserve resources that we can assume the variability impact of renewable generation is exactly the opposite and always less than the benefit of the same controllability in demand response and we can assess the value of demand response using this inequality as a guide.

1.8.1 Generation Variability

On the supply side of the reliability equation we find that variability in renewable resources is the most significant contributor to uncertainty in the overall generation production scheduling process. Current renewable generation forecasting tools are based on five technologies: numerical weather prediction, ensemble forecasts, physical models, empirical modeling and benchmarking, which are combined in a 3-step process to product a forecast: (1) determine weather conditions, (2) calculate power output, and (3) scale over different time-horizons and regional conditions [54]. In general, the RMSE of renewable forecasting methods grow asymptotically as the time horizon is extended with the best models having an RMSE of less than 5% for 1 hour forecasts to over 35% for 3-days forecasts. There is high variability in the reported performance of different forecasting tools. Because generation resources are dispatched based on these forecasts, the principle component of unscheduled generation deviations is the error in the forecasts of renewable resources [55].

System operators schedule generation reserves primarily as a function of the amount of generation scheduled, and secondarily based on the class of generation scheduled. Regardless of the amount or type of generation scheduled, only certain types of generation resources may serve as reserve resources, such as hydro-generation or combustion turbines. In general, base-load thermal resources such as coal and nuclear are not usable in such a manner and it is not economical to use intermittent resources such as combined cycle plants [56]. (Renewable resources are naturally excluded from consideration because they are the source of the variability.)

The output of many types of renewable electricity generation, such as wind, wave and solar, is intermittent in nature. Output varies with environmental conditions, such as wind strength, over which the operator has no control. Including these fluctuations has the potential to affect the operation and economics of bulk systems, markets, and the output of other forms of generation. It can affect the reliability of electricity supplies and the actions needed to ensure supply always equals demand. The findings of a review of more than 200 studies on impact of intermittency provide a baseline of facts upon which we can evaluate the impact of demand response control [57]:

- With additional variable generation, systemlevel operating margins must be increased unless there is a large amount of response or controllable load. Otherwise the Loss of Load Probability (LOLP) can be expected to increase. The addition of variable generation or demand response does not change the fundamentals of how LOLP is estimated.
- The contribution of variable generation to reliability is measured using the capacity credit, which describes the percentage of installed capacity reduction as the share of electricity supply from variable resources. For system with less than 20% variable generation, the capacity credit is usually 20-30% of installed capacity, but declines as the share of electricity from variable sources increases.
- Standby capacity is the amount by which system margin must increase in order to maintain reliability. This number only has meaning at the system level and should never be associated with any given variable resource. There is ongoing debate about whether LOLP fully captures the changes in reliability arising from variable generation because the number of small curtailment events may increase while the number of large outage events may remain

unchanged or even decrease. This suggests the same may be true for using LOLP to evaluate the reliability benefits of demand response.

- In liberalized markets, most of the electric energy is still traded primarily using medium and long-term bilateral contracts. The system operators make small residual adjustments using purchased short-term reserves. The costs of acquiring these short-term reserves are passed on to consumers. Variable generation typically adds up to 20% to the cost of electricity supply to provide 5-10% of the installed capacity of wind in additional supplies. In most systems this cost is typically less than \$5/MWh.
- In these markets, there is no single entity that is responsible for acquiring system margin and therefore the cost of additional margin required to mitigate the reliability impact of variable generation is difficult to estimate. There is also a need for a common definition of the system reliability cost of variable generation. Overall the reliability cost of variable generation is estimated at 10-20% of its direct cost, including the cost of maintaining a high system margin but these costs do not consider the externalities of environmental and emissions impacts. For the purposes of establishing the impact equivalence between generation variability and load controllability this may be fortuitous, as it makes it unnecessary to remove these in order to establish a solid basis for cost impacts: load controls do not exhibit these same externalities, although they may have their own different ones, such as consumer behavior impacts.

Variable resources do help reduce the need to operate fossil-based power plants, and thus reduce emissions to a first order. But this benefit is not on a one-to-one basis because the need to continually adjust fossil plant output can cause secondorder increases in emissions due to decreased plant efficiency. For 3 MW of wind capacity added, only 2 MW of fossil capacity is decommitted. Additional startups reduce the emissions benefits of wind by 2%. Part-load operation reduces the emissions benefits by an additional 0.3% in WECC [58]. In addition, at high variable generation levels, some energy may need to be spilled because there are no consumers for it under light load conditions. The effective emissions rate for wind due to these secondary effects relative to a typical interconnection fossil generation mix is about 1-2%/MWh [59].

The overall emissions penalties for renewable benefits can are shown in Table 4. Based on the variable resource impacts inequality assumption, we should assume that demand response benefits cannot exceed these values.

There are a number of considerations that limit the equivalence between variable generation impacts and controllable load benefits. In particular, the geographic dispersal of variable generation supports diversity, which is a key assumption in estimating their collective reliability impacts. For demand response, such assumptions may not hold. In addition, certain regulatory practices such as defining gate closures (the lead time required to procure reserves) may differentially affect how well improvements in forecasting of variable generation reduce reliability impacts relative to changes in load forecasting as more load becomes responsive.

1.8.2 Load variability

Time-series load data is the foundation of all load analysis. The most commonly available data on load are metered balancing area, substation, feeder, premises, and end-use load data (in decreasing order of availability). Utilities have measured balancing area to feeder-level load using SCADA systems for decades and this provides a very clear picture of the aggregated behavior of load. Most obvious in this data is the weather and diurnal sensitivity of load, which are the basis of load forecasting tools [60].

Until recently, premises load data was only measured monthly, and depending on the rate paid by the customer it might be only energy use (so-called interval metering) or peak power (for ratchet demand rates). However the advent of advanced metering technology has offered the possibility for significantly more detailed sub-hourly premises load data that allows analysts to examine many shorter term behaviors such as devices and equipment cycling at the sub-hourly horizon. Although end-use metering is still very limited, it does provide additional insights that contribute important sub-hourly information to the study of load variability [61].

Recent work has identified a distinctive spectral signature for power from wind turbines [62]. The technique was successfully applied to sizing stor-

age for variable generation mitigation [63], reducing variable generation forecast uncertainty [64], and studying load control for variable generation mitigation [65]. It particular, there appears to be an opportunity to use variability spectra to create a library of end-use load signatures that will enable the study of both load and generation variability and support the design of demand response control programs that are better suited to mitigating variable generation. This area appears to be a potentially very fruitful topic for research with numerous opportunities, including

- End-use signature development for load decomposition;
- Model identification for both duty-cycle phase and amplitude of sub-hourly load behavior;
- Identification of human-driven behavior and demand response sensitivities; and
- Identification of non-cyclic load variability phases and amplitudes for diurnal and seasonal behavior.

The response sensitivities based on spectral variability functions in particular appear to simplify the evaluation and analysis of variability generation and demand response impact questions. For example, the computation of the overall emissions or cost impact of a load shift of hours can be estimated by the convolution

$$U(t) = \int_{-\infty}^{+\infty} \upsilon(\tau) L(t-\tau) d\tau = (\upsilon * L)(t)$$

where v(t) is the cost of emissions at the time t and L(t) is the load. While in time domain this can be difficult to compute, in frequency domain it is relatively simple:

$$\hat{U}(s) = \hat{v}(s) \cdot \hat{L}(s)$$

where $\hat{U}(s)$, $\hat{v}(s)$, and $\hat{L}(s)$ are the Fourier transforms of U(t), v(t), L(t) respectively. Given a library of both generation variability and load control signatures in frequency domain, the optimal demand response design problem may be relatively simple to evaluate.

Wind	CO2	CO2	N2O	CH4	CO	NOx	SOx	PM
10%	12%	12%	9%	12%	10%	13%	8%	11%
20%	21%	21%	11%	17%	15%	22%	17%	22%
30%	28%	28%	10%	21%	19%	29%	24%	32%
40%	33%	33%	4%	23%	20%	34%	30%	40%

Table 4: Emission Reductions Relative to the 0% Wind Penetration [23]

1.8.3 Characteristics of load

Loads and load control exhibit a peculiar characteristic that is often not considered in benefits analysis. The relationship between energy, load, and ramping is actually quite robust. Most demand response programs can exclusively affect either power demand in the short term or energy consumption in the long term. In every other respect energy, power, and ramping are strictly related to each other as

$$\frac{d}{dt}Energy(t) = Load(t) = \int Ramp(t) \ dt$$

and this relationship is not affected by conventional demand response control strategies. For example, a DSM program may reduce energy consumption in the long term, but the power and ramping impact are strictly a function of how the demand response program affects energy use. Similarly, an airconditioning load curtailment program to cut peak may reduce power during peak hours, but the natural tendency of thermostatic devices to make up for short-term deficits over the long run means that long term energy use may be relatively unchanged. The characteristic time of a demand response control strategy and how the systems it controls respond are essential to understanding how well demand response will mitigate variable generation resources and the degree to which the demand response impact inequality will apply.

The argument can be made that resources with greater ramping capabilities should be considered higher quality reserve resources. In ancillary services markets, this characteristic places a premium on faster resources with downward substitutability. For this reason, demand response resource that control the power of loads are at least as valuable as generation resources with the same net power response and often more valuable because of their greater ramping response (strong downward substitutability). In fact, it seems that the principal (and perhaps the only) limiting factor on the ramping rate of demand response resources is the telecommunications latency of the control signals. The realtime market in the Olympic study had a typical delay of a few seconds in response to the market clearing event, but the market itself cycled only once every five minutes [66].

1.9 Summary of Impacts

The impacts of generation variability hence load controllability may be summarized as follows:

- Long term load forecasts have lower relative RMSE than long term than variable generation forecasts. Thus load can be expected to outperform the generation it mitigates, all other things being equal.
- Load control can be scheduled with greater reliability than variable generation and thus can be expected to outperform the generation it mitigates, all other things being equal.
- The LOLP impacts of variable generation are mitigated by load control in part by moving all controllable load out of the load impacts by outages.
- The capacity credit for controllable load can be expected to be comparable to the capacity credit for variable generation, if not better, because for every 1 MW of load that is controllable, 1 MW of generation reserve can be decommitted.
- The standby capacity reduction associated with controllable load should in principle be 100% of the active load under control.
- When controllable load is dispatched under liberalized markets, consumers become the providers of resources. This tends to divert revenue from generators to savings by consumers.

Based on the cost of variability on the supply side, this can be expected to be about 10-20% of the direct cost of electricity, and mitigates the need to provide 5-10% additional installed capacity.

- The secondary emissions benefits for avoiding startup and part-load fossil generation are expected to be 10-20% for modest levels of variable generation (i.e., ;20%) but may be significantly lower for some bulk systems, depending on conditions.
- The geographic sensitivity of load is different and very likely less than it is for variable generation. Loads tend to be more uniform and better diversified than variable generation.

1.10 Recent Trends

The trend toward a more integrated and interconnected complex energy system is inexorable. Progress on the 21st century's infrastructure of complex interlocking energy resource, transformation, information, service, social, and economic networks is challenging our current understanding of these systems and our ability to design and control them.

Significant challenges and research opportunities remain in load modeling and simulation, understanding the impact of consumer behavior on demand response, the foundational theory for controlling widely dispersed demand response resources, and the verification, validation, monitoring, and metering of demand response systems in utility operations.

Overall, it is clear that we are entering a period of increased electric utility receptiveness and growing innovation in the methods and strategies for turning a largely passive customer base into an active part of electric system operation. Technical innovation based on sound economic and social objectives as well as robust engineering design will be instrumental in bringing about this transformation.

The impact of controllable load on system operation can be deduced from studies on the impact of variable generation. The studies to date suggest that variable generation has both costs and benefits, and that the benefits outweigh the costs for reasonable mixes of variable generation relative to conventional resources. Many of the adverse impacts of variable generation are positive impacts for controllable load in the sense that the magnitude of the cost or impact as a function of generator variability is a cap on the magnitude of the benefit of load as a function of load controllability.

Controllable load exhibits the further advantage of high downward substitutability and thus can be significantly favored under liberalized ancillary service markets. This feature of controllable load suggests that well-designed ancillary service markets along with market-based load control strategies could be a very powerful combination.

Significant further research on how to structure such energy and ancillary service markets, design load control strategies, and model the systems in which they operate is required to further elucidate the benefits of this approach. Ultimately our ability to plan and operate bulk power systems that utilize such resources will depend on our ability to understand both the system as a whole as well as the details of the economic, electromechanical and human components which comprise it.

In March 2017, a study of demand response resources in California's three investor-owned utilities was published [24]. The authors evaluated the potential size and cost of future demand response resources. They addressed two fundamental questions: (1) What demand response services can meet California's future grid needs? And (2) what is the size and cost of the expected resource base for these demand response services?

Recognizing that demand response operates across a range of timescales, they proposed a new framework for analysis studies such as theirs. They developed a supply curve modeling framework to express the availability of system-level grid services from distributed resources based on automated metering data. They created a taxonomy and a framework that groups these services into four core categories to facilitate cost/benefit analysis:

- **Shape:** Demand response that reshapes customer load profiles through price response or on behavioral campaigns with advance notice of days to months.
- **Shift:** Demand response that encourages the movement of energy consumption from times of high demand to times of day when there is a surplus of renewable generation. Shift could smooth

net load ramps associated with daily patterns of solar energy generation.

- **Shed:** Loads that can be curtailed to provide peak capacity and support the system in emergency or contingency events—at the statewide level, in local areas of high load, and on the distribution system, with a range in dispatch advance notice times.
- Shimmy: Loads that dynamically adjust demand on the system to alleviate short-run ramps and disturbances at time scales ranging from seconds up to an hour.

The study confirmed that the focus on load shedding to reduce peaks should be redirected to focus more on local and distribution system needs, supporting control technology and business relationships that combine targeted fast shed with shift. This will likely require integration between policy at the CPUC and CAISO to ensure that market designs are matched with the most cost-effective pathways for demand response services. Continued work on how integrated energy efficiency, behindthe-meter storage, and demand response can lead to value across a range of categories—integrated demand-side management.

Further development may focus on efforts to integrate benefits at the system scale, on the distribution system, and at the site level using distributed resource planning. The authors did not undertake a detailed study of site-level electric bill impact or explicit distribution system service modeling dynamics. However, they did include a set of first-order estimates for the scale of benefits in these areas that are likely achievable when DR technology provides multi-scale service. Given the co-benefits for sitelevel service, the reported an increase of about 4 GW of additional demand response shedding capacity compared to a model run without co-benefits.

2 Transactive Control

This section presents a more or less chronological history of the development of what is now called "transactive control", beginning with the original conception of a homeostatic grid proposed by Schweppe et al. [25] in which a system of autonomous devices provides support to the grid by regulating their demand using ambient signals like

system frequency and local voltage. This significance of load resources was expanded on by Ihara [26] when he described the physical basis of coldload pickup behavior and showed how the intrinsic integral error feedback behavior of thermostats limits the extent to which thermostatic control of loads for demand response can be used as a resource akin to energy storage. The paper also shows how important consideration of the diversity, showing that even a first-order thermal model of individual homes yields a ring-down behavior after load service is returned. The paper also distinguishes between load outages (or curtailments) that do not cause discomfort (i.e., indoor temperatures stay within the thermostat deadband) and those that cause discomfort (i.e., stray outside the deadband). Finally, the paper also recognizes the difficulty of connecting individual-based controls to aggregate behavior, which is a problem that continues to be explored to this day in a wide variety of ways, e.g., in [21, 27, 28].

Transactive control adopts fundamental ideas about using pricing as a mechanism to optimally allocate energy resources in bulk power systems and attempts to apply them to distribution systems, with the objective of facilitating the participation of retail loads to the same extent that generators participate at the wholesale level. The original wholesale markets developed in Chile and New Zealand in the 1980's were prototypical examples of energyonly markets. Energy-only markets have since been augmented significantly in systems such as PJM, CAISO, and others, where capacity and ancillary services markets now exist as well. However, transactive control researchers have yet to described how markets for non-energy resources can be developed and operated at the distribution level.

The problem of pricing energy for electricity networks when loop flows are present was address by Hogan in 1992 [29], but has yet to be completely addressed in transactive systems. In Hogan's paper the concept of contract network was introduced to identify the contract paths that connect shortterm efficient prices for electric energy with longterm power capacity prices on transition systems. Here the sense of a contract network is somewhat different from that offered by Smith [30], where a contract "net" described the mechanism by which agents negotiated for prioritized access to a constrained computation resource. But the differences arise from the particulars of the resources and the system being optimized. The underlying concept of using a bottom-up approach that respects the physical limitations of the system is basically the same. In the case of Hogan's proposal, payments to the holder of a long-term capacity contract are just the amount that make them indifferent to power delivery or compensation through a settlement. As a result, the discovery of the price through a real-time pricing mechanisms produces the same result as a secondary market would but avoids the necessity of implementing an explicit capacity trading mechanism.

Huberman and Clearwater at Xerox PARC [31] extended the contract net concept to commercial buildings. In a field demonstration they showed that the mechanism found an equitable solution for satisfying thermal comfort problems when energy supply resources were constrained. The computational mechanism employed a blind double-auction in which agents bid on behalf of energy suppliers and consumers at a given price and avoided hidden costs such as excessive actuation.

These ideas were adopted by the Pacific Northwest National Laboratory in its demonstration for the US Department of Energy on the Olympic Peninsula [32, 33]. In this field demonstration, over a hundred residences, two office buildings, industrial loads and distributed generation resources were provided bidding agents to interact with a retail double-auction on their behalf. Devices were equipped with underfrequency load shedding controls, thermostatic controls, and other end-use controls that interfaced with bid/response controllers. The results showed significant increases in demand response as well as improved coordination of distributed resources. Among the benefits observed, the most significant were a 60% reduction in shortterm peak load and a 15% reduction in long-term peak load.

Huang et al [34] describes the design of the Pacific Northwest SmartGrid Demonstration (PNWSGD) project, also funded by the US Department of Energy under ARRA in 2009. This project involved 60,000 customers from twelve utilities in five states in the northwest region of the US. The project implemented an end-to-end system from generation to consumption, built around an infrastructure of newly deployed smart meters. The objective was to demonstrate how transactive control can coordinate distributed generation and demand response, and

test a hierarchical but decentralized control system where each node of the power grid used local signals of demand and price to match supply with demand at varying frequencies of up to every five minutes or less.

Melton et al. [35] summarized the transactive control research under the PNWSGD Project. In the context of the project transactive control may be thought of as extending the notion of locational marginal pricing throughout the power system from generation to end-use. The transactional nature of the technique, however, introduces a new element in the use of a pair of signals to implement an equivalent to market closing distributed in space and time. This was achieved using a negotiation process, but it was shown to not always converge. The PNWSGD project was very ambitious and was largely successful although it did not achieve all its stated objectives. Some utilities were not fully successful in deploying all their technologies, and some deployments did not provide the expected financial or operational returns [36]. The final report does not make any determination regarding the causes of problems that were identified, and made no attempt to diagnose them.

Modeling and simulations of these systems remain a crucial requirement for transactive program development, and require tools that can model simultaneously the markets, the power system, and the end-use loads. Fuller et al. [37] examined demand response and dynamic pricing programs, which have played increasing roles in the modern smart-grid environment. The authors argue that price-driven response programs are only a relatively recent development. While active markets may allow customers to respond to fluctuations in wholesale electrical costs, they may not allow the utility to control demand as precisely as more conventionally deployed direct load control systems. Transactive markets using distributed controllers and a centralized auction can create an interactive system that may limit demand during congestion events, but otherwise does not subject consumers to utility control during normal operating periods. The advent of computing and communication resources has created the opportunity to deploy transactive demand response programs at the residential level, where the combination of automated bidding and response strategies, consumer education programs, and new demand response programs give the utility the ability to reduce demand and congestion in a more controlled manner.

The transactive system protocol and dynamic control mechanisms require modelers to capture load variation, stochastic signal losses, consumer fatigue and limits on control signals that arise out of physical constraints. Jin et al. [38] showed that the control mechanism can perform adequately in adjusting the aggregate supply-demand mismatch. and is robust to steady transactive signal losses. They developed a large-scale network simulation model for evaluating such a hierarchical transactive control system as part of their work on the Pacific PNWSG demonstration. In this simulation the transactive control system communicates local supply conditions using incentive signals and load adjustment responses using feedback signals in a distributed fashion in order to match the consumerdesired load to the utility-desired supply scenario.

Transactive technologies include such things as "micro-tagging" of resources, more use of distributed intelligence, and dynamic transaction routing and approval. Ipakchi et al. [39] presents a broad concept for the Smart Grid of the future that requires coordinated management of large numbers of distributed and intermittent resources, while maintaining high degrees of grid reliability, cost-effectiveness and efficiency. This concepts involves a high-degree of information exchange between operating entities, devices, and users to facilitate scheduling, dispatching and control of intermittend generation, energy storage and demand response resources using a variety of energy and ancillary services markets. The authors call for new methods that provide real-time end-to-end management of the system. They argue that deregulation of wholesale electricity markets provides a framework in which to consider this more easily. But they also argue that recent technical advances facilitate extending this framework to a "transactive framework" that supports scheduling, dispatching and control using competitive markets.

Additional resources can be made available in such systems by using conventional commercial building automation systems. Transactive control has been shown to apply to any thermostatically controlled device with one- or two-way communication, and shows qualitatively the value of the market-based controls. Katipamula [40] makes the case that as electricity demand continues to grow,

traditional approaches to meet the demand would require significant additional demand response resources, and that transactive control of residential resources is not sufficient. Part of the solution must come from "smart" commercial buildings as well. As with most residential buildings, many commercial buildings lack the necessary infrastructure to participate in transactive systems. Building on the work of Huberman [31] and others, the authors describe market-based transactive controls that can be implemented in an existing building automation system (BAS) with little or no additional capital expenditure and show how one can make commercial buildings more demand responsive.

Pratt [41] presents the key motivations and design considerations behind the development of a real-time pricing tariff approved by the Public Utility Commission of Ohio (PUCO) for AEP's gridS-MART demonstration project [42]. The design of a revenue-neutral real-time price rate that reflects locational marginal prices from the wholesale market addressed the key desire to combine both wholesale and retail congestion costs at the distribution feeder level. This simultaneously and seamlessly managed peak loads at both the feeder and system levels. The tariff included an attempt to address key issues related to equity and providing credits and incentives for congested periods by providing a congestion rebate. The authors estimated the expected impacts on customer bills, which were considered by the PUCO when it approved the real-time price tariff.

In addition to pricing, consumers can be rewarded for tolerance to service delays and reductions, especially when engaging micro-grids and electric vehicle-to-grid services. Scaglione et al [43] describes Demand Side Management (DSM) and Demand-Response (DR) programs that are aimed at revealing the intrinsic elasticity of consumer electricity demand and make it responsive to the nearterm cost of supplying generation. The authors argue that DSM and DR are indispensable for balancing the market power of generators and reducing the need for reserves. But they also recognize that the debate on the right approach to integrating DSM and DR in system planning and operation is not yet closed, with transactive mechanisms being a leading contender among approaches that can aggregate smart loads, properly account for inconvenience costs, and modulate the total demand time optimally while converging to the energy dispatch.

Widergren et al. [44] argue that the most exciting aspect of the smart grid vision is the full participation of end-use resources with all forms of generation and energy storage in the reliable and efficient operation of an electric power system. Engaging all of these resources in a collaborative manner that respects the objectives of each resource, responds to global and local constraints, and scales to the large number of devices and systems participating is an unsolved problem. The American Electric Power Northeast Columbus gridSMART RTPda project demonstrated distributed decision-making system approaches. As a multi-feeder extension of the Olympic project, the Columbus project demonstrated a scale-up of residential demand response that uses the bidding transactions of supply and end-use air conditioning resources communicating with a real-time, five minute market that balanced the various needs of the participants on a distribution feeder. Running as a summer peak-load system in PJM ISO territory, the project provided valuable additional field data that complemented the Olympic data set.

The problems (and solutions) are not all technical. Sahin and Shereck [45] classified the costs and benefits of renewables for all market participants using the Transactive Energy Framework proposed by the GridWise Architecture Council in 2013 [46]. They raise some of the concerns that restructuring the system pose. As renewable generators start to replace conventional resources and more and more customers begin to produce their own energy locally, there is a growing concern over market access parity. As more consumers become "prosumers" and the utility is left with a diminished role and must maintain the grid with declining revenues. Those who cannot afford their own renewable sources pay for critical infrastructure costs with higher rates. They conclude that the current market mechanisms cannot properly distribute the costs and ensure grid reliability.

Many important questions remain outstanding regarding the best approach to improving the grid. Bowes and Beehler [47] make the case that the concept of an integrated grid is the natural next step in the evolution of bulk power systems. New fast and ubiquitous digital communications technology and evolving regulatory policies enable both an integrated power grid and a transactive energy system. The integrated grid uses legacy electric systems as the platform for incorporating all the new distributed and renewable resources. But they ask if consensus is reached on whether and how the legacy system allows planners and operators to adopt new technologies that are so physically and financially inter-dependent at a scale and level of performance otherwise considered impossible. Is it a safer, more reliable and more affordable system? Have we established the value proposition for a highly integrated system that makes transactive energy possible and eventually desirable? Can we leverage all the available resources to improve the utilization of all the legacy grid assets?

Sved et al. [48] examined the role of demand side management in providing ancillary services to the network. However, the use of demand resources for ancillary services has traditionally been limited because of a lack of field demonstrations that test whether we can rigorously quantify their ability to support grid reliability requirements. The provision of fast-acting frequency control from demand-side resource was simulated using Kok's PowerMatcher [49] in combination with real-time power control hardware. In a parallel study [50] they argue against assuming that all the flexible devices within the network must be managed and controlled under one demand-side management scheme. They explore what happens when two independent demand side management schemes control a portfolio of flexible devices. They use their findings to propose a methodology to analyze the performance of nonhomogeneous control schemes using their real-time power hardware-in-the-loop co-simulation platform, and recommend this type of co-simulation as the basis for investigations of ancillary service benefits.

Sandoval and Grijalva [51] proposed a platform to coordinate distributed energy resources as part of a building model framework to help integrate renewable resources. The platform is based on a decentralized approach the employs the concept of electricity prosumers, economic agents that both produce and consume grid products and services. An important aspect of their approach is a layered architecture reminiscent of the network stack in the Internet: a physical layer, a local control layer, a cyber layer, a system control layer for economic dispatch and real-time control, a market transactive layer for integration and a business layer for costs and revenues. The platform enables coordination between spatially and temporally distant systems with heterogeneous resources. The coordination is maintained dynamically while accommodating both end-user and system constraints. Their results show that using such a coordination platform supports higher amounts of renewable energy while it reduces carbon emissions and operational costs.

Such highly interactive coordination requires more reliable and higher throughput communication infrastructure. In considering the impact of the Internet on power systems, Collier [52] quotes Bob Metcalfe, the inventor of the ethernet and wellknown technology visionary:

Over the past 63 years, we met world needs for cheap and clean information by building the Internet. Over the next 63 years, we will meet world needs for cheap and clean energy by building the Enernet.

The analogy to the impact of the Internet on information technolocay has created high expectations for energy networks. Revolutionary advances in electronics, telecommunications and computing technologies, and devices and applications are expected to transform how we design and operate bulk electric power systems. What started as an information network connecting people is now a system of systems connecting devices as well—an Internet of Things. According the Collier, the U.S. electric utility model is arguably becoming non-viable and may be supplanted by many smaller interconnected networks of increasingly autonomous systems with literally millions of distributed generation, storage, and energy management nodes. This new more distributed but still highly interconnected grid of smart interacting devices is growing more ubiquitous, powerful, economical, and secure. Collier argues that the Internet of Things is the *sine qua non* platform for the future smart grid or, using Metcalfe's phrasing, the "control plane for the smart grid".

In a lecture to the American Control Conference in 2016, Jakob Stoustrup [53] described what he termed an augmented "Transactive Control and Coordination" framework that builds on Collier's model as well as the previously demonstrated transactive control paradigm. This operating model was tested in the large-scale demonstration in the Pacific Northwest region of the United States [36]. The results exhibited many of the characteristics predicted from models and simulations made prior to the start of operations. But he also argues that such demonstrations have only served to illustrate the need for a more rigorous understanding of closed-loop behavior and more systematic approaches for choosing appropriate control parameters in such a framework. System modelers and designers still lack the theoretical underpinnings needed to fully understand the impact of closing the loop around market-like mechanisms using many local conventional autonomous closed-loop systems built on a large number of aggregated controllable devices.

Behboodi et al. [54] discuss the integration of plug-in electric vehicles in smart grids from different perspectives. In order to achieve a grid-friendly charging load profile, a strategy is proposed based on the transactive control paradigm. This charging strategy enables electric vehicle owners to participate in real-time pricing electricity markets to reduce their charging costs. Then, the impact of large-scale adoption of electric vehicles on electricity generation and inter-area flow schedules is discussed. In order to quantify potential changes, an interconnection-scale optimal scheduling problem is used to determine hourly tieline flows. Given price sensitive loads, the objective function of the scheduler maximizes the total social welfare. Finally, fastacting demand response for frequency regulation is used to reduce the need for generation ramping. This supports high penetration levels of intermittent renewable resources by maintaining the short-term balance of energy supply and demand.

Galvan et al. [55] developed the concept of "transactive energy" as an instance of transactive control for efficient electric vehicle grid integration and management. The goal is to minimize the charging cost of EVs and mitigate the adverse effects of intermittent generation resources. The study recognized also that electric vehicle charging can result in undesirable behaviors such as transformer overloads and aggravated evening demand peaks. Using the transactive energy paradigm, a distribution system operator generates "distribution locational marginal prices" at constraint nodes that are sent to each customers house. Consumer needs and resource availability are updated allowing the operator to recalculate prices in response to changing patterns of supply and demand.

One important benefit of transactive control is an improvement in the self-healing and self-managing aspects of system operations. Patterson and Geary

[56] explore these concepts for distributed networks; e.g., renewable energy nano-, micro- and macro grids. Working up from the building level through utility scale systems, and including aggregators and system operators, they describe how power sources, loads and storage of all types that are interconnected can facilitate real-time transactional power management of power flows in the network grid. They propose a variety of practical aspects of real-time transactive energy management, including software that uses modern communications technology to host the development of a new energy marketplace. They suggest that we require a platform to integrate system planning and operations, including fault detection/location, automated feeder and line switching, and automated Volt/VAR control. If such a platform enables market-based transactions by communicating in real-time with equipment, using any communication network, then this effectively turns every transactive device in the system into a revenue-grade point-of-sale terminal.

This concept necessarily should include the growing number of electric vehicles. Behboodi et al. [57] argue that smart grids can help Plug-in Electric Vehicles (PEV) manage their load in a grid-friendly way. They consider the case of PEVs participating in a retail double auction electricity regulation market using transactive control. Price-responsive charging of PEVs are modeled under real-time retail price signals. Then PEVs can defer charging or even discharge when the retail prices are high enough, e.g., when feeder capacity constraints are active. For the most advanced charging strategies, as the price rises, demand from PEVs drops, and if the constraint causes further price increases, the PEVs can begin to supply energy. The results show that when rooftop solar energy is available, transactive bid-response vehicle charging strategies significantly enhance short-term electricity demand elasticity and can reduce consumer energy costs by more than 75% in comparison to the unresponsive charge case.

But these strategies do not come without challenges for the utilities. Localized congestion problems are expected, particularly as rooftop solar PV and fast EV chargers become more prevalent. Hu et al. [58] developed a network-constrained transactive control method to integrate distributed energy resources (DER's) into a power distribution system with the purpose of optimizing the opera-

tional cost of DER's and power losses of the distribution network, as well as preventing grid problems including power transformer congestion, and voltage violations. A price coordinator is introduced to facilitate the interaction between the distribution system operator (DSO) and aggregators in the smart grid. Electric vehicles are used to illustrate the proposed network-constrained transactive control method, and the problem is solved using mathematical models that describe its operation. Using simulations, they show the effectiveness of the proposed method, and particularly how it guarantees optimality.

Rahimi and Albuyeh [59] consider lessons from transmission open-access with the increasing availability of distributed energy resources and smart end-use devices finding their place as transactive agents in the electric system. As the transactive paradigm at the retail/distribution level grows to accommodate new market participants, they see a number of parallels between the deregulation of the wholesale transmission sector in the mid-1990's and the opening up of the distribution grid to accommodate these new participants. This includes new notions such a Distribution Locational Marginal Prices (DLMP), which function much like wholesale LMPs, particularly in distribution systems where flow reversal and meshed flow are likely to occur.

Amin et al. [60] propose how the installation of a battery storage system along with a PV system in transactive systems might reduce a consumer's electricity bills. In an approach that parallels other transactive PV strategies (e.g., [57]) they propose to control the charging and discharging cycle of the proposed battery in a transactive system. Using a new cost-benefit analysis method specifically for solar energy systems when combined with batteries, they quantify the economic benefit based on realtime electricity rate and battery cost, to give an exact idea of returns and yearly savings to consumers on their investment. Using real load and generation data they show how an integrated 4kW PV unit reduces the power mismatch between the load demand and solar generation. The result shows that storageenhanced consumers can maximize their savings considerably on solar investment.

Most recently, Hao et al. [61] expanded on the transactive control approach for commercial building heating, ventilation, and air-conditioning (HVAC) systems for demand response. They describe the system models and parameters using data collected from a commercial building located on the Pacific Northwest National Laboratory campus. They show how a transactive control market structure works for commercial building HVAC systems, and describe its agent bidding and market clearing strategies. Several case studies are performed in a building controls testbed and calibrated with an EnergyPlus simulation model. They show that the proposed transactive control approach is very effective at peak shaving, load shifting, and strategic energy conservation for commercial building HVAC systems.

3 Hierarchical Control

This section presents a discussion of how demand response operates in the current hierarchical control of electric power systems and the requirements that transactive control systems must meet to help integrate demand-side resources into system operation.

The electric power industry has undergone a fundamental restructuring over the past 30 years, transforming from a regulated to a market-oriented system. Restructuring has entailed unbundling of vertically integrated organizations into independently managed generation, transmission and distribution systems. As a result, electric power markets have been divided into wholesale and retail systems that interact according to a well-defined, albeit *ad hoc* designs.

The wholesale power market design proposed by the U.S. Federal Energy Regulatory Commission (FERC) in its April 2003 white paper [62] encompasses the following core features: (1) central oversight by an independent system operator (ISO) or regional transmission operator (RTO); and (2) a two-settlement system consisting of a day-ahead market supported by a parallel real-time market to ensure continual balancing of supply and demand for power. The objective of an ISO/RTO is to ensure that supply equals demand at every instant, while maintaining system security and reliability and minimizing the total cost of serving the system demand. Optimization is performed on multiple time-scales. The day-ahead settlement system is a pure financial market for generators and load serving entities to create financially binding operating schedules. The real-time energy market allows for the physical exchange of power and addresses deviations between actual real-time conditions and contracted day-ahead agreements. The ISO solves security constrained unit commitment (SCUC) and economic dispatch (SCED) problems in both dayahead and real-time markets to determine cleared supply and demand, and corresponding locational marginal prices (LMPs), which are reported to market participants. Additionally, to maintain operational balance at any given instant, the ISO runs a balancing reserve market in parallel with the energy markets to calculate the cleared reserve capacities, and the corresponding reservation prices.

Retail markets have not gone through such a restructuring process. Hence, there is limited participation by distributed assets in wholesale markets through aggregators and no direct participation by smaller assets at all. However, this can be expected to change with accelerated deployment of new "smart grid" infrastructure such as digital meters and advanced distribution control systems as were promoted under the Smart Grid Investment Grants starting in 2009. Additionally, FERC Order 755 now requires grid connected short-term storage devices to be treated equitably as conventional generation units when providing regulation services [11]. Similarly, FERC Order 745 requires energy payment of demand response resources at nodal LMPs [12]. As a result a number of wholesale markets now allow distributed assets limited participation in energy markets, usually to meet peak load reduction or emergency services for large-scale demand response programs that serve commercial and industrial users. Feeder level resources still do not participate in wholesale markets, except when provided by demand response aggregators and a limited number of pilot/demo projects, e.g., the Olympic [32, 33], PowerMatcher [49], Columbus [42], and Pacific projects [35]. In order to realize the vision of an integration demand response system at the wholesale level, it will be necessary to consider market design changes, the development of more fullfunctioning system of retail markets, and the integration of the two that provides suitable incentives for wholesale participation by distributed assets.

There are two key elements to any proposed infrastructure that will facilitate smooth and reliable operations. The first is inter-scale infrastructure that allows devices at various levels to cooperate in determining the efficient allocation of the available resources. The second is the multi-temporal infrastructure that allows devices to shape the allocation they have received within the time horizon in which it is allocated.

The inter-scale infrastructure addresses resource allocation and is used to reconcile supply resource constraints with demand requirement, e.g., feeder constraints versus consumer comfort settings at the retail level. This is accomplished by using real-time prices, such as was demonstrated in the Olympic and Columbus projects. These systems established retail markets that discovered the retail price at which supply equals demand at each feeder in the distribution system, given the current day-ahead prices and prevailing conditions on the feeder and in the homes equipped with price-responsive devices. The Pacific project used a variant of this design for resource allocation that relies on mid-term forecasting usage instead of committing to short-term usage. This system substitutes an index for a price to avoid some of the adverse misconceptions associated with markets in an area that has none at present. This index was developed using a negotiation process that was shown to not converge (see Appendix ?? for one solution to this problem). The Pacific project also differs from Columbus project in the way the formulated signal is presented to the devices.

The inter-scale structure is shown in the vertical dimension of Figure 1, while the inter-temporal structure is shown in Figure 2. At the interconnection level we find the wholesale markets and system operators who set hourly prices and inter-area flow schedules by setting control area import/export schedules that maximize each area's ability to maintain system balance without exceeding interarea flow limits. Control areas establish local prices and respond to deviations in schedules and frequency by sending control signals (A) to generators and utilities. These interact with loads and load aggregators using the local closed-loop bid/response pricing mechanisms implemented at the distribution feeder level.

The real-time and day-ahead market-based feeder and area management systems aim to maximize asset participation at every level in the real-time and day-ahead markets by incorporating the smart grid resources into standard ISO/RTO market structures. This is achieved by solving an optimization problem subject to feeder and area level operational constraints and uncertainties of intermittent renewables and distributed smart grid assets. At the wholesale system level, the ISOs and BAs receive aggregated net load demand, supply bids for distributed assets from the area management systems and generator power supply offers from generators and aggregators. The ISO also runs balancing reserve markets in parallel with the energy and capacity markets to procure reserve energy and capacity to maintain system stability. The cleared or scheduled power setpoints and reserve capacity requirements are then dispatched to the area controllers, which in turn dispatch requirements or price signals to the feeder controllers and distributed assets in their respective retail markets.

Maintaining operational balance at every instant requires balancing areas to solve an area-wide optimization problem to allocate a portion of their reserve capacity requirements to each feeder based on the resources available. This problem is theoretically amenable to treatment by a market-based process because of the primal-dual nature of the optimization in question. This process must also maintain adequate area-wide support of frequency and tie-line flows by committing resources to autonomously mitigate deviations in the area control error. Feeders bid resources into the area market and use the cleared prices to dispatch setpoints in real-time to the distributed assets and primary devices needed to meet the performance requirements of the area and feeder control systems.

At the device level, decentralized control schemes for the distributed assets provide both economic and reliability responses based on self-sensing of frequency, voltage, broadcasts of imbalance signals, current and future prices, and local device conditions. The distributed assets must be dynamically influenced via dispatched control set-points that area reset periodically based on price signals from the retail markets, while responding autonomously and instantaneously to events during contingency operations.

The current standard practice for both direct and indirect control of thermostatic load relies primarily on so-called "one-shot" or direct load shedding strategies for emergency peak load relief only. This approach uses a controllable subset of all loads in a particular class, e.g., water heaters or air conditioners, which are transitioned to a curtailed regime that reduces the population average power



Figure 1: Hierarchical Transactive Control System Diagram.



Figure 2: Inter-temporal data flow diagram.

demand of the end-use category. After a time, these responsive loads are released and return to their normal operating regimes. This strategy is known to exhibit fluctuations in aggregate load during the initial response as well as demand recovery rebounds after the loads are released, particularly when thermostatic loads are engaged. To mitigate this behavior, direct load control strategies are sometimes enhanced by either centralized diversification mechanisms, such as using multiple subgroups of the responsive loads dispatched in a sequence that smooths the overall response of the load control system [63], or distributed mechanisms, such as using stochastic control strategies [64]. Many of these mechanisms require some knowledge of the aggregate thermal response of the buildings in which the loads are operating [65]. To solve the more general tracking problem where load "follows" intermittent generation [66], these mechanisms must address response saturation and loss of diversity [67], high sensitivity to modeling errors and noise [68]. and stability considerations due to feedback delays [69, 70].

Aggregating building thermal load is known to provide a potentially significant resource for balancing purposes [71]. But the hysteresis of standard strategy was proposed to overcome some of the mod-

thermostats requires a switched-mode representation of the individual building thermal response, which in turn gives rise to more complex aggregate load models. The hysteresis also requires that models include so-called "refractory states"; i.e, states are locked in or out for a certain time after a state transition [72]. These time-locked states are associated with transition delays rather than thermal parameters. Tractable state space models of aggregate loads can be obtained using model-order reduction strategies that linearize the system model and limit the number of state variables required to represent responsive loads [21, 73]. These models depends on knowledge of the rate at which devices turn on and off and cross the hysteresis band limits, as well as the rate at which the control lockout times expire. Such a state space model minimally represents any thermostat with non-zero deadband. More recent models include the "battery model" [74], which presents aggregate thermostatic loads as simple first-order systems. But these models are intended for small signal response such as frequency regulation, and may not be as useful for sustained peak load curtailment or emergency load shedding.

An alternative thermostatic controller design

eling issues arising from the lockout time delays, while not compromising the role of control hysteresis in limiting fast-cycling behavior of thermal loads [75]. This thermostat design uses a discrete-time zero-deadband $(T\Delta_0)$ concept that has no refractory states and synchronizes the state transition times with an external signal such as a price coming from a real-time retail double-auction. By using suitably selected sampling rates to limit fast-cycling of equipment $T\Delta_0$ thermostats were hypothesized to give rise to a simple aggregate load model and were shown to have the same comfort and cost savings as conventional thermostats when operated under real-time price tariffs.

Demand response is becoming a more accepted¹ and important option for utilities to mitigate the intermittency of renewable generation resources [76]. Transactive control is a multi-scale, multi-temporal paradigm that can integrate wholesale energy, capacity, and regulation markets at the bulk system level with distribution operations [77]. Under the transactive control paradigm, retail markets for energy, capacity, and regulation services are deployed to provide a parallel realization of wholesale markets at the distribution level. In spite of the conceptual similarity, the behavior of retail markets differs significantly from that of wholesale markets and remains an active area of research [78]. In particular, load behavior usually dominates the behavior of retail systems, which contrasts with wholesale systems where generation is dominant. In addition, there are a number of important processes in bulk power interconnection operations that have yet to be integrated fully into the transactive paradigm. Two very important such processes are system frequency regulation and control area import/export schedule tracking.

Frequency regulation and schedule tracking are jointly regulated using a feedback signal called "area control error" or ACE. The standard mechanism is based on a computation performed in time-domain independently in each control area by evaluating

$$[Q(t) - Q_s] + B[f(t) - f_s],$$
(1)

where Q(t) is the actual net exports from the control area at the time t, Q_s is the scheduled net exports, B is the frequency bias, f(t) is the interconnection frequency at the time t, and f_s is the nominal or scheduled frequency. In most realizations the ACE signal is updated by the SCADA system about every 4 seconds and further passed through a smoothing filter so that it changes with a time-constant well in excess of the generating units' fastest response; e.g., 30-90 seconds, with the purpose of reducing wear and tear on generating unit governor motors and turbine valves [7].

Numerous studies examining frequency regulation resource performance using diverse loads have been conducted in recent years. Lakshmanan et al. [79] studied the provision of secondary frequency control in electric power systems based on demand response activation on thermostatically controlled loads in domestic refrigerators in an islanded power system. Observations of household refrigerator response time, ramp rate, and consumer impact show that they provide sufficient fast responsive loads for DR activation, with a typical response time of 24 seconds and a p.u. ramp down rate of 63% per minute, which can satisfy the requirements for primary frequency control.

Vrettos et al. [64] proposed a frequency control scheme designed to augment generation response with load responses, and separate fast-acting load resources from slower responding ones to provide efficient frequency and inter-area power flow using loads. By separating autonomous residential refrigeration loads from dispatchable waterheaters and HVAC systems they achieved the desired response without compromising comfort. The separation of the loads was based on device characteristics, such as thermal inertia and significant time-dependent power variation, if any. Secondary frequency control is provided by coordinating the runtime of these heterogeneous resources. The solution shown in Figure 3 was demonstrated using an optimizer that satisfies the worst-case reserve requirements without violating end-user comfort constraints. This result provides a useful existence proof, which is significant for any transactive approach that relies on similar mixes of resources but achieves the solution using a distributed system.

Zhong et al. [80] developed a large-scale coordination strategy for electric vehicles, battery storage and traditional frequency regulation resources for automatic generation control. Recognizing that response priorities and control strategies for these resources vary with different operating states, they

¹For example, wholes ale markets now support demand response in several ISOs and jurisdictions, including PJM, California, and New York.



Figure 3: Area control scheme using loads proposed by Vrettos et al. [64]

showed that a coordinated control approach not only fully utilizes each resource's advantages but also improves the frequency stability and facilitates the integration of renewable energy.

Falahati et al. [81] examined a model of storage using electric vehicles as moving batteries in deregulated power systems as one way to deal with the frequency regulation problem in a deregulated system with a growing share of intermittent generation resources. They enabled a vehicle-to-grid option for the control of the frequency using an optimized fuzzy controller to manage electric vehicle charging and discharging based on system frequency. The results illustrated satisfactory performance for frequency control of the grid system and verified the effectiveness of the approach for reducing the need for under-frequency load shedding to protect the system against large frequency excursions.

Teng et al. [82] proposed a framework to quantify and evaluate the impact of electric vehicles on island systems like Great Britain. This framework used a simplified power system model to analyze the effect of declining system inertia on primary frequency control and the ability of electric vehicle chargers and batteries to provide resources to mitigate that impact. Using this model they proposed an advanced stochastic scheduling tool that explicitly models the loss of inertia and assesses the costs and emissions arising from primary frequency control as well as the benefits of having electric vehicles provide primary frequency response. The results of an analysis for Great Britain show that integrating electric vehicles in the primary frequency control system can significantly reduce anticipated cost and emissions growth.

But the results from additional control are not always ideal. Biel et al. [83] examined the frequency response of commercial HVAC systems by comparing different control strategies for providing frequency regulation demand response. Aside from noteworthy performance impacts from intrafacility communications delay and control latencies, the authors also observe reductions in energy efficiency when the frequency regulation controls are more active, pointing to the necessity for combined long-term energy cost and short-term regulation response revenue to be considered jointly. In a concurrent study, Khan et al. [84] followed up on studies by Hao [74] and Sanandaji [85] of the storagelike behavior of thermostatic loads by proposing a stochastic battery model. This model provides parameters of the battery model and considers changes to the hysteretic thermostatic control in response to frequency. This provides a relatively simple solution to modeling aggregate load control. However the approach has not been integrated with transactive approaches, and may not account fully for the longer-term endogenous energy conserving integral error feedback that is intrinsic to thermostatic control in general.

A number of studies of optimal generation control design have been previously reported. Bevrani and Bevrani [86] studied the general frequency control tuning problem for multiple objectives and proposed three methods for tuning PID controllers to improve the performance of closed-loop systems, including a mixed $\mathcal{H}_2/\mathcal{H}_\infty$ optimal design method. This approach is easily transferable to a static output feedback control implementation, as is the case with power system area control and any generalized extension where export schedule tracking is desired. The \mathcal{H}_2 -optimal design method is particularly interesting when there are significant robustness issues to consider, although the authors did not present a solution to the synthesis of an optimal area controller. Jay and Swarmy [87] also recently proposed a reinforcement learning-based approach to automatic generation control that was found to minimize frequency deviations by incorporating thermostatic demand response control strategies.

4 Demand Response in Organized Markets

FERC issued Order 745 in 2011 to amend its regulations so demand response resources with the capability to balance supply and demand can participate in organized wholesale energy markets as an alternative to generation resources. The order introduced requirements that (1) dispatched demand response resources satisfy a net-benefit test, and (2) demand response resources are compensated for the services they provide to the energy market at the locational marginal price (LMP). This approach for compensating demand response resources was intended to "ensure the competitiveness of organized wholesale energy markets and remove barriers to the participation of demand response resources, thus ensuring just and reasonable wholesale rates" [12].

Critics of Order 745 have pointed out that demand response is essentially unlike generation because it is exercised as a call option on the spot energy market, the value of which is the LMP minus the strike price, which in the case of retail consumers is the tariff rate [88]. Others contend that the value of demand response is the marginal forgone retail rate [89]. However it is valued, the question remains whether FERC Order 745 effectively guarantees double compensation for demand response by providing responsive load both the cost savings from energy not provided by the retailer and an LMP payment for not using same increment of energy. Such a signal might lead a firm to halt operations even though the marginal benefit of consuming electricity exceeds the marginal cost at LMP. In his comments to the Commission during prosecution of the order Hogan argues that "the ideal and economically efficient solution regarding demand response compensation is to implement retail real-time pricing at the LMP, thereby eliminating the need for [wholesale] demand response [compensation]" [88].

These arguments are largely academic if demand response cannot be deployed broadly for technical reasons. To resolve the technical questions regarding the large-scale feasibility of demand response in the context of smart grid the Olympic and Columbus demonstration studies were conducted in 2006– 2007 and 2013, respectively. The objective of both studies was to address the technical questions regarding the so-called "price-to-devices" challenge [90] by demonstrating the transactive control approach to integrating small-scale electric equipment with utility electric power distribution system operations as a first step toward integrating distributed generation and demand response into wholesale operations. Transactive control thus refers to a distributed resource allocation strategy that engages both electricity suppliers and consumers using market-based mechanisms at the retail level for the purpose of enabling demand response by the utilities at the wholesale level [91].

A number of problems were identified following the Olympic and Columbus demonstrations. The most significant among these were the following.

Short-term Price Stability When demand response resources become scarce, price volatility increased. This creates an undamped feedback that resulted in rail-to-rail actuation of the demand response resources. The oscillation develop because resource state diversity is defeated by the larger price signals, which in turn drives large price volatility. The individual resources themselves are not adversely affected by these undamped oscillations. But from the system perspective this is regarded as an undesirable regime. The oscillations continue until either sufficient demand resources are returned online to restore state diversity that overcomes
the oscillations, or the resource constraint that drove the price surge goes away.

- Lack of Forward Prices The expectation price and price volatility should be obtained from forward markets. In the demonstrations they were developed from historical responses of the system. This created a form of delayed feedback that could give rise to long term price instability.
- Lack of Multi-level Market Integration The retail markets should not be operated autonomously or in open loop. Although the wholesale prices were used in formulating the feeder price bids, at no point was the retail market used to formulate bid or forecasts for the wholesale market.
- Lack of Integration With Regulation System The retail market-controlled resources should be used to arm and reset regulation services, such as fast-acting demand response with autonomous controls. These resources should be controlled by adjusting setpoints based on resource needed at the system level. For example, grid-friendly appliance controllers were set to shed load at 59.95 Hz with a probability of 1.0. This resulted in a fixed

adjusted based on system need during each dispatch period.

aggregate control gain that could have been

Despite of these problems, the demonstration projects were largely considered technical successes. In fact, it can be argued that our understanding of these issues is in large part due to the level of complexity attempted by the projects.

Without aggregate load control, introducing price-responsive demand requires engaging millions of very small participants in the unit-commitment and economic dispatch process. This may be impractical due to the computational complexity of the process just for the thousands of larger suppliers already involved. Strategies for addressing this challenge generally involve aggregation at the retail level that enables the integration of demand units by proxy of a reduced number of larger representative units [64].

Using markets to solve electricity resource allocation problems at the wholesale bulk system level is well-understood [92]. But transactive control takes the idea to the retail level by enabling the resource allocation problem at the distribution level first before integrating it at the wholesale level. These markets are designed to find a Pareto-optimal allocation of distribution capacity, distributed resource and demand response to resolve how much wholesale resource is required, and determine how much distributed generators produce, and customers consume in the coming time interval. The transactive control systems demonstrated use distribution capacity markets to determine the energy price that minimizes the imbalance between supply and demand for electricity by participating equipment during the next operating interval [93]. The system computes a 5-minute retail real-time price (RTP) that reflects the underlying wholesale locational marginal price (LMP) plus all the other distribution costs and scarcity rents arising from distribution capacity constraints. The real-time price comes under a new tariff designed to be revenue neutral in the absence of demand response.

Distributed generation, load shifting, curtailment and recovery are all induced by variations in realtime prices. In doing so, the transactive control system can reduce the exposure of the consumers and the utility to price volatility in the wholesale market and the costs of congestion on the distribution system [94]. Retail prices are discovered using a feeder capacity double auction that can be used to directly manage distribution, transmission or bulk generation level constraints, if any. Distributed generation is dispatched based on consumers' preferences, which they enter into an advanced thermostat that acts as an automated agent bidding for electricity on their behalf. Thermostats both bid for the electricity and modulate consumption in response to the market clearing price. By integrating this response with a price signal that reflects anticipated scarcity the system closes the loop on energy consumption and can improve resource allocation efficiency by ensuring that consumers who value the power most are served first. At the same time, consumers provide valuable services to the wholesale bulk power system and reduced energy costs at times of day when they express preferences for savings over comfort.

In the California ISO, demand response is acquired using two different products, Proxy Demand Resource (PDR) and Reliability Demand Response Resource (RDRR) [95]. PDR bids supply in CAISO energy, non-spin and residual commitment markets for economic day-ahead and real-time dispatch. RDRR bids supply for reliability purposes as energy services only and dispatches economic day-ahead and reliability real-time.

In the eastern interconnection, PJM obtains demand response services from Curtailment Service Providers (CSP). CSPs are entities responsible for demand response activities in PJM wholesale markets [96]. These can be companies that focus exclusively on customer demand response capabilities, or they can be utilities, energy service providers, or other types of companies that can provide the necessary services to PJM. PJM uses these services to obtain two kinds of demand response, economic and emergency response. Customers can participate in either or both, depending on circumstances.

PJM treats emergency demand response as a mandatory commitment which is dispatched similarly to generation when reliability resources are in short supply or under emergency operating conditions. Four products are generally used: (1) Limited DR for no more than 6 hours a day on up to 10 days during summer months, (2) Extended Summer DR for no more than 10 hours a day for up to 10 days during extended summer months, (3) Annual DR for no more than 15 hours a day for any day of the year, and (4) Base DR for up to 10 hours any day of the year. Pricing is driven by the capacity market as defined under the Reliability Pricing Model (RPM), with payments made monthly for availability during expected emergency conditions.

In contrast, PJM economic demand response is a voluntary commitment to reduce load in the energy market when wholesale prices are higher than the monthly net benefits price at which the benefit of reduction exceeds the cost of paying for the demand response. These resources are used to displace generation and PJM expects these resources to reduce load measurably, and impose penalties for loads that fail to deliver the expected load reductions.

Economic demand response resources can also provide Ancillary Services to the wholesale market if enabled with the appropriate infrastructure. These include (1) Synchronized Reserves that act within 10 minutes of dispatch, (2) Day-Ahead Scheduling Reserves that act within 30 minutes of dispatch, and (3) Regulation that follow PJM's regulation and frequency response signal. Participating in the Ancillary Services market is voluntary, but once cleared in the market, performance is mandatory.

Demand response programs in New York (NY-ISO) and Texas (ERCOT) have many similar characteristics and products. But the specifics of their designs only further demonstrate how no two wholesale markets use precisely the same rules and definitions. This only exacerbates the existing Balkanization of the North American energy market designs and presents yet another barrier to the widespread adoption of demand response as a technology to mitigate the reliability impacts of renewable intermittency.

4.1 Retail Competition

Retail competition was introduced in Europe, Australia, New Zealand and some US states over the last two decades. The theoretical rationale for retail competition goes against conventional wisdom in retailing because electricity is not a storable good and the infrastructure needed for retail delivery is largely a natural monopoly. Furthermore, the homogeneity of electricity limits opportunities for potentially profitable retailing activities such as presentation, packaging, bundling, and co-branding. These combine to limit the benefit of introducing retail competition in three signicant ways [97].

- 1. The potential demand for a supplier to meet is limited by the low revenues that retailing activities can generate.
- 2. Retail markets must be created where none exist today, which requires consumers to engage in searching, learning, and transaction activities that are costly barriers to switching from the incumbent utility.
- 3. The homogeneity of the products limits the differentiation and discrimination necessary to create value-added services for the consumer.

The expectation was that entrepreneurial innovation would provide social benefits and would overcome these barriers. Retail competition was expected to reduce market imperfections [98], motivate the discovery of new products and services [99], stimulate customer awareness, and drive competition in generation [100]. But the results seem not to be supported by the data observed initially. One key indicator is that the percentage of customers active in the market remains quite low: no retail market reports more than 50% participation and a majority reported less than 10% by 2009 [97]. Moreover, switching costs have not decreased over time, suggesting that learning effects are not intensifying and customers are not reducing the risks and uncertainties in their decisions. In Great Britain and Norway, for example, the costs of switching did not fall below 10% by 2009 [101], while the rate of customer switching remains high [102] compared to other markets.

In California another form of retailing has emerged called "Community Choice Aggregation" or CCA [103]. CCAs allow cities and counties to combine the demand of electricity customers in their jurisdictions to procure electricity through bilateral contracts or markets. The advantage a CCA has relative to a regulated investor-owned utility (IOU) is threefold. First this gives the community served more control over the energy sources used and allows the CCA to market a differentiated product (e.g., renewable energy) that the incumbent IOU cannot provide due to regulatory constraints. Second the CCA may not be required to purchase the same level of "firm" resources, which may be a significant costconsideration for renewable energy sources. Finally, a CCA presents consumers with some choice in purchasing electricity under a cooperative structure, in spite of the fact that it is not individual choice in the manner envisioned by retail competition advocates.

The result of retail competition and community aggregation overall is mixed. There is an ongoing segmentation of the retail market into participating and non-participating consumers, which is undermining any persistent generalization of retail competition and community choice in electricity delivery. Regulators are justifiably concerned that underserved and low-income communities are not wellserved by retail competition and community choice, even when they choose not to adopt it for themselves, partly because as those who can afford to flee the regulated utility environment do so, those who remain behind are left with most of the costs that are not recovered by these new solutions. Nonetheless, the incumbent utilities still retain significant "brand loyalty" where retail competition has been adopted, and for those consumers who are unable or unwilling to participate it is not at all obvious that they have received much benefit from the transformation of the retail marketplace.

5 Scheduling, Dispatch and Regulation

Responsibility for the reliability of electricity interconnections is shared by all the operating entities within each interconnection. In a traditional power system, these entities are vertically integrated. A committee process involving all the entities within each power pool establishes the reliability criteria utilities used for planning and operations. Typically, the operating entities belong to larger regional coordinating councils so that they can coordinate their criteria with neighboring power pools. Since 1965 these regional councils have been organized under what is now called the North America Electric Reliability Corporation (NERC), which establishes the recommended standards for system reliability [2].

With the evolution toward market-based operations in recent decades, vertically integrated operating entities have been broken up into generation companies (GENCOs), transmission owners (TRANSCOs), load serving entities (LSEs), and energy traders that do not own assets, all of whom are collectively the market participants [104]. The responsibility for ensuring the reliability of a control area is delegated to independent system operators (ISO) or regional transmission operators (RTO). In general market participants have a duty to provide accurate data about their assets and costs as well as follow the dispatch orders of the ISO/RTO. The ISO/RTO has the duty to ensure that each market participant meets the reliability rules and determines the dispatch orders necessary for the electricity supply and demand to match according to NERC's reliability standards. This system is predicated on a successful competitive market in which private decentralized trading and investment design work to allow substantial commercial freedom for buyers, sellers and various other types of traders [4].

The method used to implement such a system planning and operating model employs a twostage process referred to as the unbundled or twosettlement approach:

1. Unit-commitment (UC) is a days-ahead process that determines the hourly operating set points of the generation assets based on their bid energy prices and the forecast system load. 2. Economic-dispatch (ED) is an hours-ahead process that determines the real-time generation schedules and procures additional supply to ensure system reliability.

This approach can be used for both regulated and unregulated markets and the analysis method is similar for both short-term operations and longterm planning with only the caveat being that ISOs must perform the system studies for deregulated markets to determine whether additional generation and transmission may be required.

Overall the timeframes for planning and operations can be separated into the following security functions [5]:

- 1. Long term planning (2-5 years) determines needed investments in generation and transmission.
- 2. Resource adequacy (3-6 months) secures generation to serve expected load and sets long-term maintenance schedules.
- 3. Operation planning (1-2 weeks) coordinates short-term maintenance schedules and longlead generation.
- 4. Day-ahead scheduling (12-24 hours) performs a security-constrained UC using energy bids.
- 5. Real-time commitment and dispatch (5-180 minutes) performs real-time security-based economic balancing of generation and load.

For time-intervals shorter than about 5 minutes, the reliability of the system is delegated entirely to the generation and loads according to reliability standards promulgated by NERC and coordinated separately by each interconnection.

Modern bulk electric interconnections are constrained by the physical requirement that electric energy is not stored in any substantial way during system operations. Historically, utility operations have focused on controlling generation to "follow" load and ensure that at every moment supply exactly matches demand and losses. To make electric utility planning and operation economical and manageable, the industry divides generation resources into three principal categories: base load, intermediate load, and peak load [7]. Base load generation is the bottom portion of the supply stack that essentially runs uninterrupted throughout the year (except during maintenance or unplanned outages). Intermediate generation runs continuously but only seasonally as the diurnal load nadir rises and falls. Peak generation is the supply that must be started and stopped daily to follow the diurnal load variations. Each of these types of generation also provides regulation and reliability resources to help control frequency and respond to contingencies and emergencies in generation and transmission operations.

For decades load had not generally been considered part of the overall planning and operations model of electric interconnections except to the extent that its growth set the conditions for capacity planning. But in recent years increasing thought has been given to the role that load can play as a demand resource that (1) reduces the need for new conventional generation resources, (2) avoids using generation resources in inefficient ways, and (3) enables the addition of generation resources that exhibit substandard performance characteristics when operating under the conventional loadfollowing paradigm [7].

Today the term "demand resource" encompasses a wide range of products, services and capabilities related to the control and management of load in electric systems. Prior to the advent of "smart grid" technology, demand resources were primarily considered for planning purposes, such as demandside management (DSM) programs, and very limited operational purposes such as in extremis underfrequency or under-voltage load shedding programs (UFLS/UVLS) [105]. DSM programs are planning programs that focus on energy efficiency and other long-term demand management strategies to reduce load growth so that the need for significant new generation capacity investments can be deferred or eliminated. Generally these programs pay for themselves by reducing capital costs for a number of years, possibly indefinitely. DSM programs helped the industry transition from its pre-1970s 7% annual capacity growth to the sub-3% growth prevalent today in modern electricity interconnections.

But DSM programs have a number of long-term limitations that prevent their application to other system planning or operations objectives. First, energy efficiency is generally a diminishing return because every additional dollar invested replaces less inefficient load. In addition, DSM programs can give utilities an incentive to substitute investments in a few larger (presumably more efficient) base load units with numerous smaller (generally less efficient) intermediate units or even (typically very inefficient) peaker units. Finally, DSM programs generally do not provide the capabilities and controllability needed to address some recent new planning and operations challenges such as generation intermittency, the lack of transmission capacity investments, evolving load characteristics, new ancillary service market designs and short-term/real-time energy price volatility [106].

In contrast, UFLS and UVLS are strictly operations programs that focus on very short-term load curtailments under severe contingencies. They are used when all or part of the electric interconnection is threatened by a large unexpected loss of generation or system separation that creates a power imbalance which can only be remedied by drastic and immediate reductions in load.

Load shedding programs also have important limitations because they are pre-programmed actions armed to respond to specific circumstances identified during planning studies. They are not the flexible and graduated responses needed for more general regulation and balancing operations. Load shedding programs also tend to indiscriminately disconnect loads and do not have the ability to affect only less critical end-uses such as air-conditioners and water-heaters.

As intermittent generation becomes a standard element of the generation fleet, the interest in using demand response as a substitute for new controllable generation can be expected to grow. In addition, demand response has long been regarded as necessary because it reveals the elasticity of demand in ways that mitigate supply-side market power.

But the mismatch in the characteristic size of loads, their timing, and their uncertainty relative to conventional generation is a significant obstacle to using demand response to simultaneously displace supply-centric reliability services and mitigating generator market power: there are relatively few easily observed generators and their characteristic response times are relatively slow compared to overall system dynamics. Loads in contrast are far smaller, far more numerous, and for more difficult to observe. But they are potentially far faster acting than the overall system dynamics [7]. The physical

and temporal scales of resource variations are shown in Figure 4, and we can see where demand response and renewable generation intermittency time scales match well, while the physical scale does not.

Bulk power system planning, operation, and control have generally been designed to consider the characteristics of generators and treated loads as a "noisy" boundary condition. Thus load control remains quite difficult to incorporate into bulk system planning and operation. In general, the approach to addressing this fundamental mismatch is to devise demand aggregation strategies that collect numerous small fast acting devices with high individual uncertainty into a few large slower acting aggregations with reduced uncertainty. While not requiring every electric customer to participate in wholesale markets, demand aggregation provides a means of increasing consumer participation in system resource allocation strategies market-based or centrally controlled and thus can mitigate price volatility whether for energy, capacity, or ramping services [107].

From an economic perspective, aggregating electricity customers can be viewed as a means of capturing consumer surplus to increase producer surplus, by segregating consumers into groups with different willingness to pay. Three general approaches are usually employed to creating consumer aggregation for either operational or economic objectives:

- 1. Economic aggregation is achieved using price discrimination methods such as different rates for different customer classes, product differentiation, and product or service bundling strategies.
- 2. Social aggregation is achieved using various subsidy programs, and other social group identification strategies such as environmental, green or early-adopter programs.
- 3. Technical aggregation creates technical structures that either directly aggregate consumers, or indirectly enable economic or social aggregation. Technical aggregation can be accomplished using service aggregators, creating technological lock-in with high barriers to entry or exit, or constructing local retail markets independent of wholesale energy, capacity, and ancillary service markets.



Figure 4: Control and resource variability physical and temporal scales

Variable or intermittent generation is a growing fraction of the resource base for bulk power systems. The variable character of certain renewable resources in particular is thought to undermine the overall reliability of the system insofar as forecasts of wind and solar generation output have greater uncertainty than more conventional fossil, nuclear or hydroelectric generation resources, or even load. As a result, the expectation is that while variable renewable generation resources do displace the energy production capacity of fossil power plants, they may not displace as much of the power or ramping capacity of those plants. Consequently, the variable nature of renewable resources may indicate that they do not offer as much emissions benefit as expected if one were to assess their impact simply on energy production capacity [108].

It seems intuitive that demand response should be able to mitigate the capacity and ramping impacts of variable generation by reducing the need to build and commit fossil generation to substitute for reserves or ramp in place of fast-changing renewable generation. But this substitutability is constrained by (1) the nature of variable generation, the role of forecasting, and the impact of resource variability on the emissions and economics of renewable resources; (2) the nature of load variability and how demand response is related to load variability; and (3) the characteristics of end-use demand and the impact of demand response on energy consumption, peak power and ramping rates over the various time horizons that are relevant to the variable generation question.

Taken together, these constraints and interactions provide the basis for assessing the economic and environmental impacts of controllable load and demand response resources on various time scales. It is by virtue of the downward substitutability of reserve resources that we can assume that the variability impact of renewable generation is exactly the opposite and always less than the benefit of the same controllability in demand response, and we can assess the value of demand response using this inequality as a guide. Taken as a whole, this assessment of the current situation and the benefits of demand resources for energy, capacity, and ramping response provide a basis to justify a major investment of load as a resource and the infrastructure needed to integrate it with the system as a whole.

5.1 Technical Requirements

The remainder of this section focuses on the technical requirements to realize a broad vision of what is now called more generally "Transactive Energy", which is based on the original transactive control concept but encompasses the entire energy system. The approach is based on a multitude of market-like mechanisms used to discover the prices that most efficiently schedule, dispatch, and regulate system resources. The concept is proposed as the long-term solution to the challenge of transforming the power grid into a 21st century system that meets 21st century needs.

What is missed by most of the existing literature is the strong connection between scheduling, dispatch and regulation on the one hand, and the degeneracy of energy, power and ramp control² on the other hand. Having recognized this problem, the designers of transactive energy infrastructures suggest ten key elements required to successfully implement a complete transactive control system. The breadth of these requirements reflects not only the high complexity and difficulty of the overall design problem, but also the broad scope of the concept itself. These requirements cover the following processes:

- 1. Incentive policies and market mechanisms;
- 2. Market-based services;
- 3. Device-level controls;
- 4. Retail-wholesale integration;
- 5. Inter-temporal coordination;
- 6. Balancing services;
- 7. Balancing area control;
- 8. Feeder control;

- 9. Integrated autonomous and market operation; and
- 10. Off-normal operation.

5.1.1 Incentive Policies and Market Mechanisms

Control policies and market mechanisms should provide the correct incentives for the full range of distributed assets. These assets must be able to express their ability, willingness, and desire to modify their supply or demand and respond to the system's overall conditions as they change over time. These policies and markets must lead to the discovery of prices and provide incentives for participants to share accurate data that leads to a coordinated device response and precisely meets the needs of the grid, as a function of time and location, from the lowest-cost resources available. More specifically, a range of incentives and resulting bidding strategies must align with operational and capital costs, applicable in both vertically-integrated and restructured market environments, to ensure appropriate levels of customer participation. This must take into account the utility revenues needed to justify the investment in, and operation of the interconnection as a collection of independent financial and operational entities with both cooperative operational goals and competing financial goals.

5.1.2 Market-based Services

Current market structures do not support a level playing field for distributed assets when compared to conventional generation. The proposed paradigm seeks to create an equitable market mechanism for coordinating and controlling all system assets through a distributed, self-organizing control paradigm that protects customer choice but encourages and coordinates participation. This is the purpose of the so-called "transactive" paradigm. Distributed smart grid asset participation in the wholesale market must be coordinated through a hierarchical architecture of nested market mechanisms. This requires the design of retail markets, but leaves the actual functional control at the device level. This also allows load-serving entities (LSEs) to play their natural role as a resource aggregator in the retail markets and paves the way for independent

²Control degeneracy is the recognition that one cannot independently control the energy use, power level and ramp rate because each is the derivative of the previous.

third party aggregators to develop optimal portfolios to sell to the utilities.

This does not necessitate complete structural changes to current ISO/RTO day-ahead and realtime structures (system level). Rather it complements them by providing institutional mechanisms that integrate retail and wholesale markets using continuous feedback controls. At each of the hierarchical levels (feeder and area), available resources – whether demand or supply, whether energy, capacity, or ancillary services – are aggregated from the level below while considering local constraints, such as energy allocations, capacity limits and ramping reserves. Device level bids are aggregated by feeder level management systems while applying local constraints by clearing retail capacity markets such as those demonstrated in the Olympic and Columbus projects.

The feeder level bids are then cleared by the area level markets, which submit aggregated or residual bids into the ISO/RTO wholesale market. Conversely, the area and feeder markets then receive the cleared price and dispatch quantities from the ISO/RTO, which are eventually passed down to the end-use customers. This forms a feedback mechanism for a closed-loop, multi-level optimization problem that engages distributed assets in the wholesale market.

The same structural formulation is applied in both ahead and real-time markets. The only difference between ahead and real-time markets is the formulation of agents' optimization problems and the source of the information needed to formulate bids. When using forward markets, each resource bids using residual allocations of quantities from longer-term markets.

5.1.3 Device-level Controls

At the lowest level devices use price and other information to autonomously determine appropriate actions and apply their own constraints to local control processes. In the Olympic and Columbus demonstrations of this approach HVAC loads responded to changes in normalized prices by adjusting the thermostat set-point utilizing smart thermostat and smart-meter technology, as illustrated in Figure 5. These devices bid the price point for their on/off decision as well their power quantities into a retail market. The price point is a function of the difference between the desired air temperature and the current air temperature and the quantity a function of recent metering. Customers are actively engaged with a simple user interface that allows them to choose how much demand response they provide from a range between "more comfort" and "more savings" with a simple slider control. This parameter k allows consumers to determine the level of market participation. They can always override the response by either changing the bid response curve or removing the device from the market altogether, provided they are willing to pay potentially higher prices were they to occur. This approach protects customer choice, while continuously rewarding participation. The Olympic project extended this concept to commercial VAV control units, as well as municipal water pumping facilities, and various types of distributed generating units.

Similar device bid and response mechanisms must be created for other distributed assets, including distributed storage, distributed generation, and smart appliances. The US Department of Energy's Office of Electricity and General Electric Appliances [109] showed the benefits of multi-objective controls for distributed assets for a wide range of devices. The end result would be an environment and a set of rules for participation where vendors can create additional bidding and control strategies, depending upon the goals of the customer, ranging from relatively simple to highly complex optimization routines or predictive algorithms. Design of device level controls and bidding strategies forms the basis for their participation in retail markets. Equitable treatment of distributed assets in the wholesale markets is accomplished through retail-wholesale integration as described in the following section.

At the device level, distributed assets should provide multiple services at different time scales: (1) respond to market prices both ahead and real-time, (2) respond to imbalance signals, and (3) respond autonomously to reliability needs inferred from ambient frequency and voltage signals.

Autonomous responses are critical for many reliability purposes where there may not be time to communicate needed actions through a wide-area network. Appliance and equipment manufacturers are rapidly moving toward mass production of devices with smart grid capabilities that can be leveraged for this purpose. However, utilities and balancing authorities are hesitant to support such de-



Figure 5: Thermostatic device control with price-based bid feedback for a cooling regime using comfort control k.

ployments, because the response of fleets of such devices has not been fully integrated with their control schemes for grid stability. Distributed assets must be equipped with autonomous controllers and include settings to arm them according to instructions from feeder, area or system levels. In this way, the autonomous immediate response of devices can be continuously tailored to system needs, such as low system inertia due to high on-line renewable generation and inverter-based loads.

To provide the multiple services, at the device level, distributed assets must be equipped with multi-objective control strategies designed to enable single resources to provide multiple benefits to the system. These control strategies must be accounted for in the coordination problem, for example, by using receding horizon optimization techniques (viz. model predictive control). Device level controls introduced in previous demonstrations must be expanded by including similar easy-touse (from the customer perspective), economically driven responses for all smart grid assets, including other smart appliances, storage, and distributed generation to provide cost-effective, controllable solutions.

5.1.4 Retail-Wholesale Integration

One of the main objectives of this paradigm is to offer a comprehensive framework that fully integrates retail and wholesale power markets. This framework must provide a way for end-users (distributed assets) to contribute indirectly in wholesale markets.

Retail market designs must not only facilitate interactions between end-users (distributed assets) and the feeder level management system. The feeder level management system must coordinate the behaviors of the distributed assets within their respective retail markets, as well as consolidate the net offering for area and wholesale markets. This provides an avenue to inject local constraints, which are often overlooked when solving system-wide problems using distributed resources. Feeder level optimization and control for a real-time retail market was demonstrated during the Olympic and Columbus projects. In both of these projects, system-wide constraints (in the form of wholesale market prices or LMPs) are coupled with local constraints (local feeder capacity) to clear retail markets and provide both local and system-wide benefits using demand response resources, as illustrated in Figure 6. Effectively, the system enables customers to reduce their energy consumption during high price events to reduce energy costs, while coordinating devices



Power quantity



Figure 6: Storage resource allocation using retail markets. The battery charge bid (1) is accepted while its discharge bid (2) is not, even though the feeder appears congested.

Figure 7: Aggregate resource allocation using area markets. Feeders supply and demand curves are combined to determine resource participation factors.

responses during localized congestion events to decrease demand and deploy local resources, providing a system for equitably rewarding customers for participation. Distributed generation and storage similarly bid into the retail market, subject to run time constraints (e.g., a maximum number of allowable run hours). While successfully showing that distributed assets can participate in retail level markets, the distributed assets in these projects did not affect the wholesale price—they only reacted to wholesale prices and local constraints.

The feedback loop is closed by integrating retail markets through to wholesale energy, capacity and ancillary service markets. This allows distributed assets to interact with the wholesale market through the feeder's retail market and area level management systems. Price and availability information must flow from the device level to the feeder level retail aggregators and markets. The feeder level markets combine individual device bids, including battery demand/supply bids for charging/discharging, as shown in Figure 6.

Similarly, aggregators combine the supply bids from distributed renewables to form feeder level supply curves. The aggregate net constrained results of the demand and supply are bid to the area level management systems, which combine various feeder level bids in a similar manner to the ISO/RTO's wholesale market. Once the wholesale market clears, the cleared prices and quantities are reported back to the area and feeder level markets, which apply their local constraints through appropriate bids to clear their respective markets.

This successive multi-level clearing process is illustrated in Figure 7 by the feeder level to area level market integration. Based on the day-ahead wholesale market LMP, day-ahead feeder bids and other regional resources, the area market determines an area day-ahead price and available capacity of area power and establishes the area's scheduled net load and generation commitment. Thus the area forward market incorporates day-ahead supply bids from renewables and load bids from feeder to determine the day-ahead area price. The real-time feeder markets then clear the local supply and demand to determine the feeder price that meets the area's scheduled loads, storage and distributed generation. Storage devices then charge or discharge depending on the cleared price. In many cases endusers' bidding processes may include learning capabilities [110] and must simultaneously report supply bids to participate in ancillary services markets to realize incentive compatibility under the two-part operation of those markets.

Wholesale markets must be operated by an ISO/RTO such that they facilitate the interaction between the ISO/RTO operators and the area level markets. Conventional and grid-level largescale renewable generation fleets also operate directly in the wholesale markets. The ISO clears the wholesale market using the conventional methods of security-constrained unit-commitment and economic dispatch (SCUC/ED).

At the area level, agents gather multiple feederlevel resources bids, combine bids and determine possible area-level resource constraints, and derive area market prices. At this level, distributed asset constraints are no longer considered, because they are embedded in the bids from the feeder level markets. In response, area controllers produce market prices that are received by the area level management system. The optimal bidding strategies problem of the area markets must be modeled as a mathematical program with equilibrium constraints. The outer problem of this bi-level problem is the area level management system's optimization problem while the inner problem is the ISO's optimization problem. The wholesale market clearing process depends on bids provided by agents and entities at all levels, but interacts only with area markets at the next level down. The bids in turn must be formulated based on market clearing processes at both wholesale and retail layers. The integration of retail and wholesale markets in this manner enables participation of distributed assets. The design of retail and wholesale markets is the same in both dayahead and real-time markets with only the direction of information flow differing in the two markets.

5.1.5 Inter-Temporal Integration

Day-ahead markets are operated as pure financial markets, allowing participants to enter financially binding contracts that hedge against the price volatility of real-time markets. Because a significant majority of the energy, capacity and ancillary service resources are committed under these financial agreements, the real-time markets effectively serve as energy, capacity, and ramping imbalance markets by determining the price at which the residual must be acquired. As long as the cost of uncertainty is sufficiently higher than any emergent arbitrage op-

portunity, the incentive to commit a majority of resources in forward markets will be sustained and the quantities emanating from those markets will serve as reliable forecasts of supply and demand for all required resources and capabilities. The principle of the two-settlement system will be preserved by this design and in fact could be extended for longer-term horizons if desired.

Distributed assets must be induced to enter into contracts to procure or sell most of their energy, capacity and ramping resources in the day-ahead markets. The residual resources and needs are then submitted in the real-time markets when more precise information on the prevailing conditions becomes available. The real-time markets will also serve to correct the unforeseen imbalances between contracted day-ahead conditions and actual real-time positions. The horizontal information flow between retail and wholesale market, and their respective entities; viz., feeder-level and area-level management systems, must be addressed in a manner similar to distributed assets.

In the presence of high levels of renewable and distributed assets, economics cannot be the only objective for utilizing distributed resources in an effective manner unless reliability can be directly translated into costs, which seems unlikely at this time. Markets and bid/control strategies for balancing services must run in parallel with retail and wholesale energy and capacity markets in both day-ahead and real-time markets. The market clearing mechanism used in the wholesale markets clear balancing reserves by co-optimizing energy and balancing needs. The balancing reserves must be determined endogenously, based on energy demand and supply, rather than set as hard limits, as is the norm in most interconnection operations today.

5.1.6 Balancing Services

The effectiveness of autonomous, grid-friendly response by smart appliances in the form of underfrequency load shedding has been already demonstrated in the Olympic project. Fifty pre-existing residential electric water heaters were retrofitted and 150 new residential clothes dryers were deployed. These responded to ambient signals received from under-frequency, load-shedding appliance controllers. Each controller monitored the frequency of the power grid's ubiquitous 60 Hz AC voltage signal at the outlet. The controllers reduced the electric load of appliance whenever electric powergrid frequency fell below 59.95 Hz. The controllers and their appliances were installed and monitored for more than a year at residential sites at three locations in Washington and Oregon. The controllers and their appliances responded reliably to each shallow under-frequency event, which occurred on average once per day and shed their loads for the durations of these events, typically about a minute and never more than ten minutes. Appliance owners reported that the appliance responses were unnoticed and caused little or no inconvenience.

There are a few more recent demonstrations of the provision of ancillary services with aggregated distributed assets such as demand response in buildings. Lawrence Berkeley National Laboratory teamed with PG&E and SCE/Oak Ridge National Laboratory to demonstrate how residential air conditioning programs could be used to supply spinning reserves to CAISO in 250 and 2500 homes, respectively [106]. Ecofys led a demonstration for Bonneville Power Administration and utilities in the Pacific Northwest region to show how regulation could be provided for "firming" wind using water heaters, thermal storage furnaces, refrigerated warehouses, and commercial building HVAC [111]. A Steffes water heater and three electric vehicles are supplying regulation for PJM in ongoing demonstrations [112]. PNNL conducted an analysis that showed electric vehicles could supply all additional ancillary services for integration of 30% of generation from wind in the Pacific Northwest region [113].

A reliability safety net created for the ISO/RTO operation can be very valuable. It would comprise fast-acting smart grid assets that can be armed and disarmed based on the clearing of a bulk-level ancillary service market and area balancing markets. These distributed assets should be aggregated into a grid-friendly network of actively managed autonomous devices that self-sense frequency and voltage fluctuations, and respond to broadcast set-point signals from control area regulation markets. These assets must provide the full range of today's ancillary services and more: virtual inertia, regulation, ramping, spinning reserve, and emergency curtailment capabilities.

5.1.7 Balancing Area Control

Balancing area controllers must be able to arm and disarm distributed autonomous grid-friendly devices that provide balancing services, to reduce the burden on conventional generation, particularly when increasing balancing requirements are expected during periods of high level renewable variable generation output. At the area level, the goal of the balancing supervisor is to minimize the area control error (ACE) signal, which is a weighted sum of the deviations of the system frequency and the interarea power flow. The balancing supervisor must coordinate with Automatic Generator Control (AGC) at the transmission level to provide frequency and tie line interchange support, minimizing balancing authority ACE. The balancing area control, in coordination with AGC, aims to maintain the system frequency at 60 Hz during the normal load demand fluctuation, and restore the system frequency gradually when a contingency occurs in the system. In particular, the balancing supervisor needs to maintain the inter-area power flow at the scheduled level. The inter-area power flow reference values are calculated based on differences of measured total area real power references (and reactive power required to realize the real power transfers) that were cleared by the real-time area market. The balancing control must balance the input of these two power references according to the current system operating conditions.

5.1.8 Feeder Control

Feeder control is a critical component in the entire system because it mediates between the area control and individual device controls. Its role is bidirectional in the sense that (1) it must convert the balancing objective specified by the area control into supply constraints for the retail markets; and (2) it also must represent elasticity of those assets to the area control system. Essentially, the feeder controller has two objectives. The first is to minimize a feeder control error in the local market and the second is to enable coordination of various local devices to provide reactive power support for voltage regulation.

A feeder's real power reference is based on the power reference cleared by the balance area control and the power reference from the retail capacity market. The feeder's balancing controller must reconcile these two power references according to the current system operating conditions. During normal conditions, the cleared power reference from the retail market will be given more weight. But during contingencies, the signal received from the balancing entity must be given more weight.

Additionally, the feeder controller must account for variability and uncertainty of local distributed renewable resources such as rooftop photovoltaic panels, and local constraints such as feeder congestion. After the feeder real power reference is determined, the feeder control must dispatch optimal setpoints to the autonomous devices that help maintain adequate power support. The feeder reactive power management system must collect real time feeder voltage information from all the devices involved in voltage support. Then the management system must coordinate with local device-level controllers by dispatching voltage setpoints and if necessary, suppressing the autonomous local control signals to avoid excessive voltage regulation.

5.1.9 Integrated Autonomous and Market Operation

The real-time market management system supports both area and feeder level control but it must support one additional function. As part of the cooptimization problem at each level, ancillary service contracts must be entered into on the same time scale as the real-time energy market, and weighted according to real-time energy market requirements determined by NERC reliability standards. During normal operations, the control systems will take a purely economic perspective to maximize returns, by dispatching smart grid assets either towards real-time energy needs, ancillary service needs (such as frequency or voltage regulation, spinning reserve, etc.), or a combination of both. But during disrupted or stressed system conditions, weighting functions must be adjusted to focus on short-term system stability requirements rather than long-term economic objectives. During each real-time market cycle (e.g., every 5 minutes) the control system must establish contracts for real-time energy and balancing/regulation services, and dispatch resources subject to local constraints and availability provided by device bidding. This allows the smart grid assets to participate in multiple market revenue streams under a multi-objective control problem (i.e., storage devices participating in both energy markets and frequency regulation), capturing multiple revenue streams to increase profitability and long-term sustainability. At this time scale, only contracts for reservation of ancillary services are formed, while the control itself must be performed at a much faster rate using autonomous responses, and compensated at energy, capacity, or ramping market prices.

5.1.10 Off-normal Operation

Distributed smart grid assets must be pre-armed for instantaneous autonomous response during abnormal conditions, such as loss of communications or contingency events. This allows each asset to respond to the correct extent, and avoids the amplifying system-wide voltage, power, or frequency oscillations that might follow too many devices responding. For loads that cannot continuously adjust their power use (such as water heaters, HVACs), they must be switched on/off selectively so that the aggregate of a large number of these loads provides the required droop characteristic. Distributed control strategies must be designed to coordinate the different devices so they respond autonomously while maintaining the overall stability of the system. Approaches to perform this function have yet to be developed.

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