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A survey on behind the meter energy management systems in smart grid

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ABSTRACT

Over the last few years, the fast-growing energy needs across the world have intensified a central challenge: how to reduce the generation and operation costs in power systems and, in parallel, to minimize the hydrocarbon emissions. Moreover, one-quarter of world's population still lacks access to electricity, as the cost of building conventional power grids is not affordable by third world countries. On the other hand, behind-the-meter (BTM) energy systems offer cost-effective solutions to aforementioned challenges, as they enable end-users to satisfy their energy needs with distributed energy generation and storage technologies. To that end, this paper presents a detailed survey of BTM energy management systems. The paper starts with the classification of the electrical loads with respect to their physical properties, priority ranking, and sizes. Next, the literature on BTM energy management systems is systematically classified into three main categories: technology layer, economic layer, and social layer. The technology layer spans the studies related to power systems including distributed generation and storage technologies, whereas the economic layer shows how economic incentives along with optimization and scheduling techniques are employed to shape the energy consumption. The social layer, on the other hand, presents the recent studies on how to employ social sciences to reduce the energy consumption without requiring any technological upgrades. This paper also provides an overview of the enabling technologies and standards for communication, sensing, and monitoring purposes. In the final part, a case study is provided to illustrate an implementation of the system.

1. Introduction

1.1. Motivation

Over the last decade, the power grid operations have become more stressed due to growing customer demand and less secure with the integration of intermittent renewable resources. Moreover, the usage of fossil fuels in the electricity generation raises environmental concerns all over the world. Such issues become more intense during peak hours, as the power grid runs up against its operating limits, hence becomes more fragile. One effective way to alleviate the challenges mentioned above is the deployment of smart energy management systems which integrate communication, control, and sensing technologies to shape the electricity consumption efficiently [1,2]. To that end, in this paper, we present a holistic survey on behind meter energy management systems.

The term *behind the meter* (BTM) refers to a renewable energy system located in a single building or at multiple facilities (depicted in Figs. 1 and 2) owned by a single entity i.e., university campuses, usually operated with distributed generation and storage units to supply all or some portion of the end user‘s energy demand [3,4]. Due to the uncertainties involved in distributed generation units, the critical part of BTM system is the orchestration of loads through efficient optimization and scheduling algorithms. Moreover, BTM systems are usually not connected to the bulk generation, but typically are connected to end user's meter allowing the customer to sell energy back to the utility. In this regard, behind the meter energy management systems refers to a system which fulfills the end users energy needs while realizing certain objectives such as reducing operation cost, improving energy efficiency, balancing demand and supply, and reducing carbon emissions.

1.2. Benefits

The multifaceted benefits of the BTM energy management systems are ultimately linked to the current power system operations. Power grids are large complex networks designed to deliver resources from centralized power generators (e.g., nuclear, hydro, natural gas, coal) to distributed demand. Since large-scale energy storage is still not a viable option, the generation should be aligned with the demand at every instant. To that end, utility operators dispatch their generation assets

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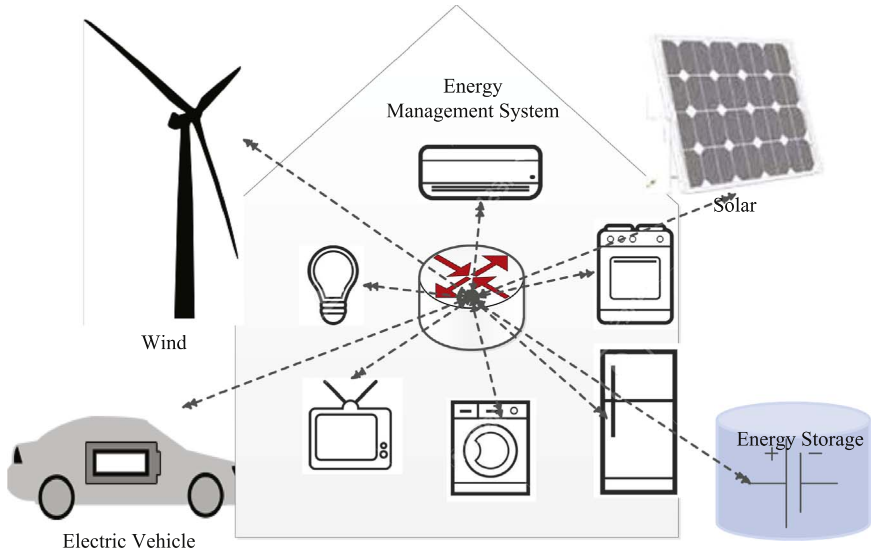

Fig. 1. Behind the meter system: case for single household.

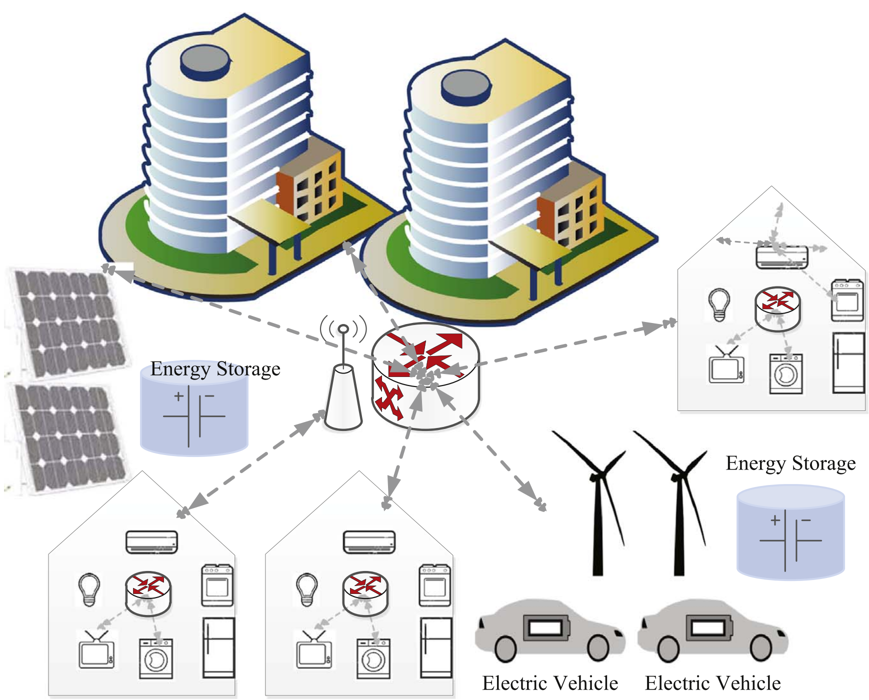

Fig. 2. Behind the meter system: case for a campus.

by considering their cost, flexibility, environmental "head-room", and distance to load. Traditionally, power system operators plan the system capacity (e.g., generation portfolio, transmission capacity, transformer ratings) according to the peak energy demand plus additional reserve margin which is typically set as 15%. Even though, this approach enables power grid to serve the customer demand with a very high reliability, it leads to inefficient use of resources as the peak generation typically occurs only around 10–12% of the time [5]. Hence, the adoption of energy management systems is aiming to reduce the usage of fast start, high cost, and usually environmentally unfriendly peak generators and promises the following benefits:

(1) *Economic Benefits:* Today, almost 40% of the residential energy is wasted due to lack of awareness in the U.S. [6]. By promoting customer-utility interaction, users can enjoy incentives and differentiated tariffs for shifting peak hour demand and they can even make a profit by selling excess local generation back to the grid. Regulators and utilities can benefit from increased utilization of grid components and lessened investments. Obviously, exact calculation of benefits depends on the assumptions made. The work in [7] shows how demand-shaping with energy storage units leads to monetary savings under different scenarios (e.g., varying utility tariffs, consumption patterns). Fig. 3 shows the average residential electricity consumption in 2014. The early adoption of BTM systems are likely to take place in regions like GCC, North American, Nordic countries, and Western Europe, as the average household consumption is relatively high compared to the world average .

(2) *Reduced Green House Gas* (*GHG*) *Emissions*: The electricity generation sector in the U.S. accounts for 32% of GHG emissions

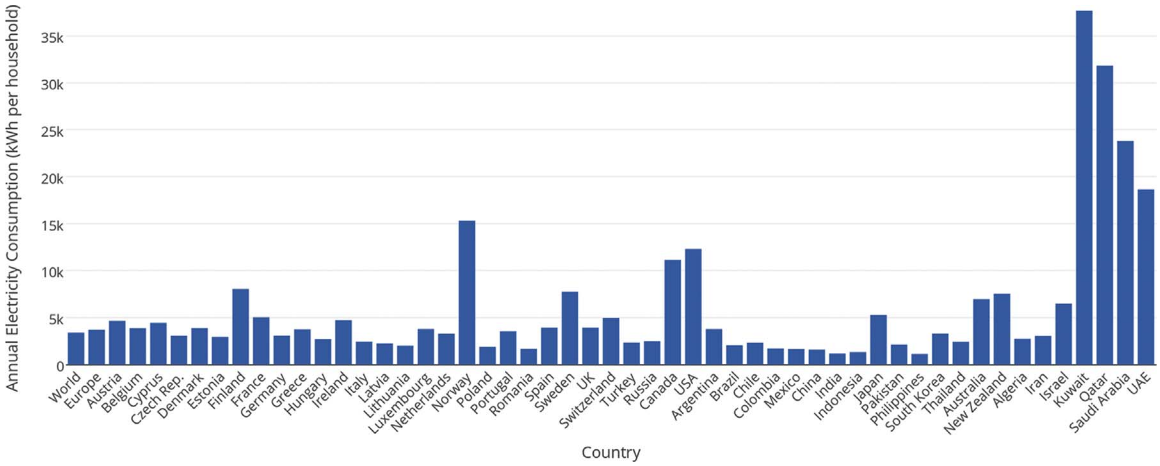

Fig. 3. Average household electricity consumption in 2014.

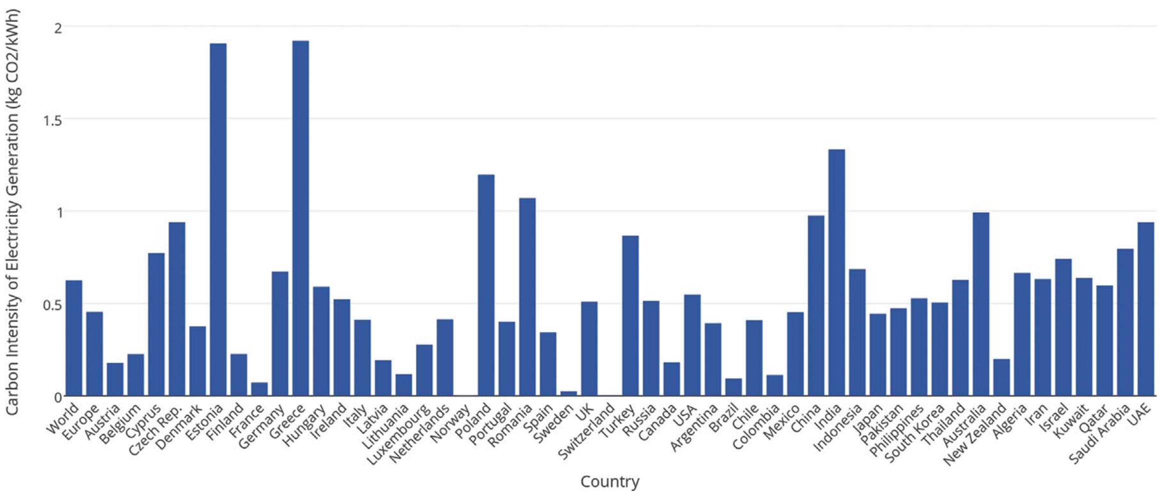

Fig. 4. Carbon intensity of power sector by country in 2011 [200].

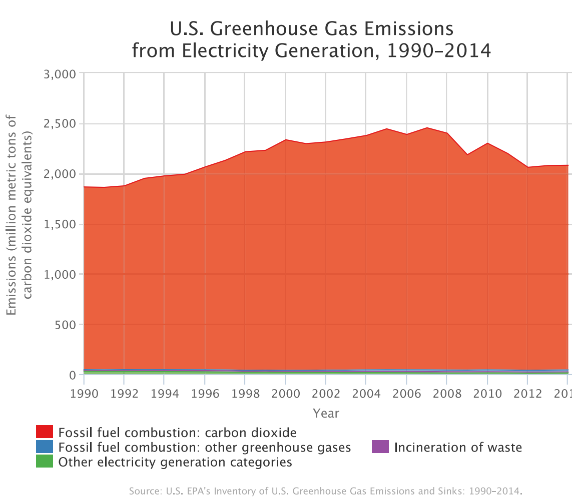

Fig. 5. GHG emissions due to electricity production in the USA.

[8], while the global emission levels from the power sector is around 42% of entire emissions [9]. Fig. 5 shows the emission levels 1990 in the US. The results reveal that the steps taken towards decarbonizing the power grid have started become effective, as the emission levels have been declining over the last few years. Moreover, carbon intensity per kWh is an important indicator of the power sector. Fig. 4 depicts a detailed overview of carbon intensity in the electricity generation for various countries. Consequently, nations with high carbon-intensity put bold renewable integration targets. For instance, China aims to generate 30% of its electricity from renewables by 2020, while India seeks to deploy 175 GW of renewables by 2022. Moreover, GCC members (Qatar UAE, Saudi Arabia) aims to generate 20% of their electricity by 2030. Energy management systems offer tremendous opportunities to cut the hydrocarbon emissions as the most pollutant generation types (see Table 1 for carbon emission levels) are employed during peak hours when the energy management is expected to be the most effective.

(3) *Deferred Grid Investments*: As the BTM energy management systems aim to reduce the stress on the grid, the required upgrades to cater for the peak demand will be postponed and occur gradually over time. This deferral will enable utilities to avoid exhaustive siting processes. Moreover, globally more than 1.3 billion people do not have access to electricity. Hence, BTM systems may be the only option for remote locations such as farms, villages as they are not connected to the main grid.

(4) *Improved Grid Resiliency and Power Quality*: Distribution generation and storage technologies along with intelligent energy management tools will reduce the mean service interruption duration and they will further protect loads against short-term effects (e.g., voltage spikes, dips, and surges). Locally generated energy user demand will be met locally and the employment of far-

Table 1
Carbon emissions [187] and electricity generation cost [188].

Technology	CO_2e/GW h	$/MW h
	(in Tonnes)	
Conventional coal	888	95.6
Oil	733	128.4
Natural gas	499	66.3
Solar PV	85	130
Nuclear	29	96.1
Hydroelectric	26	84.6
Wind	26	80.3

off high capacity generator options will be decreased. This way, congestion on transmission lines will be reduced and the corresponding line losses (in the form heat) will be minimized. According to EPRI [7], significant monetary savings can be achieved with storage units and their efficient control [10,11].

(5) *Energy Independence and Security*: The promotion of distributed energy generation and its efficient operation with BTM energy management systems make nations energy independent as the use of domestic resources reduces the dependency on foreign resources. Over the last decade, countries such as China, Germany, South Korea, and the U.S. have been expanding their renewable portfolio. For instance, China produced 30% of its electricity needs from renewable sources. [12].

Due to all of the benefits mentioned above, this trend is further supported by regulators and policy-makers, and specific targets are determined to cut the energy consumption. We present some detailed analysis in Table 2 and more detailed analysis for other countries can be found at United Nations Framework Convention on Climate Change [13].

We start out classification methodology by identifying the components of the BTM systems. The first component is defined as the loads used by consumers. Loads are classified according to their physical properties (e.g., resistive, inductive, and conductive), job types (e.g., essential, deferrable, throttleable, flexibility), and their size (e.g., home, microgrids, etc.). Next, we classify the literature on energy management into three partially overlapping layers. The first layer is the *technology layer* which includes distributed generation and storage technologies and their efficient operation, management, and control. Since adding new production and storage capacity is very expensive, the second layer spans how economic incentives can be employed to shape the energy consumption and the associated carbon emissions. This layer is named as *economic layer*, and the topics in this layer include optimization, scheduling, and control of appliances. The components of the *technology layer* often act as constraints in the problem statement of the *economic layer*. The third layer includes studies from *social sciences* which tries to understand the role of human behavior in energy consumption and proposes ways to control human behavior. This layer is relatively young compared to other two layers, but it has received some attention in the literature. The overview of literature classification is presented in Fig. 6. Also, we provide an illustrative example in Fig. 7 to summarize the three-layered approach. As shown in this figure, the *technology layer* controls the system capacity as it depends on the output of the renewable generation and the state-of-charge level of the storage unit. The *economic* and the *social*, on the other hand, matches the consumption with the system output by controlling and scheduling load.

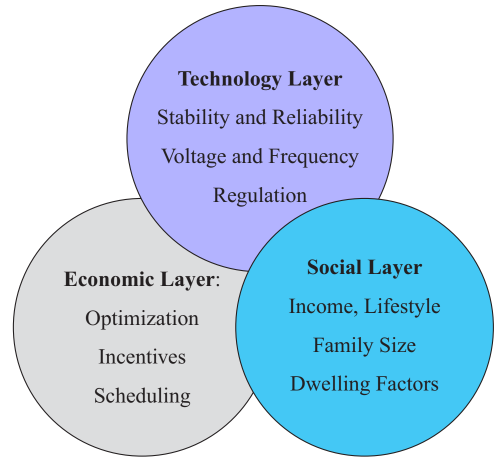

Fig. 6. Three domains determine the operation, control, and management of behind the meter energy management systems.

1.3. Contributions

A handful of surveys have attempted to discuss demand response programs from utility company point of view [14] and smart home activities [14]. Furthermore, several works provide an overview of smart grid technologies [15,16] and specifically from communication standpoint [17]. However, the scientific community recently discovered that energy management for behind the meter systems requires interdisciplinary research efforts from power systems, communications, optimization and control, economics, and sociology. Nonetheless, to the best of the authors' knowledge, this is the first study that focuses on the technological, economic, and social layers. Thus, in this study we, comprehensively address and analyze the challenges of behind the meter energy management systems from technological, economic, and sociological layers. Moreover, we systematically classify the literature till mid-2015.

2. Load classification

A typical residential unit consists of tens of electrical loads to meet the needs of the modern life. In the previous section, we presented

Table 2
GHG emissions due to electric power generation by country.

Country	% of GHG	Source-year	Reduction Target	Res. to	Deadline	Mandate/rule
Australia	33%	Australian Dept. of Environ [189]-2014	30%	2000	2020	Kyoto Protocol [189][a]
EU	31.10%	European Environ. Agency [190]-2008	95%	1990	2050	Roadmap for moving to a low-carbon economy in 2050[b]
Qatar	22%	Qatar Ministry of Environ. [191]-2013	30%	2008	2030	The Qatar National Vision [192].[c]
USA	32%	US Environ. Protection Agency [8]-2012	30%	2005	2030	Clean Power Plant Act [193][d]
UK	27%	Committee on Climate Change-2013	80%	1990	2050	

[a] This target includes Co_2 Emissions from all sectors.
[b] 95% of the electricity generation will have 0% emissions [194].
[c] Qatar's carbon emissions per capita are the highest in the world.
[d] Goal is set solely for a reduction in electricity generation.

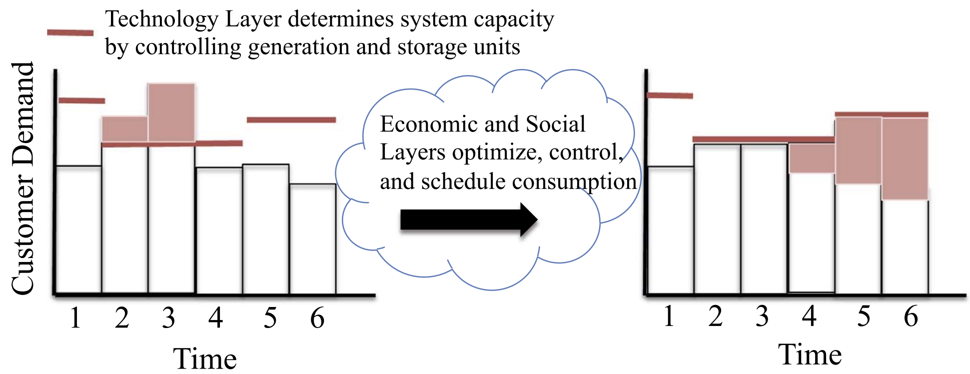

Fig. 7. Illustration of three-layered approach.

drivers that affect and shape the domestic electricity consumption. This section, on the other hand, classifies the loads according to their physical properties, job priorities, and sizes.

2.1. Classification by physical properties

Electrical loads convert electricity into another form of energy (e.g., heat, motion) that is useful for end users. Based on their physical properties, the majority of the loads employed behind-the-meter systems can be categorized into four groups [18].

(1) *Resistive electrical loads* are typically the ones that convert electric energy into heat. Loads, such as incandescent lights, ovens, toasters, coffee machines, heaters are considered to be resistive loads. Also, the electrical current of these loads is in phase with the voltage. Also, the electrical current of such appliances reaches to its steady-state value quickly.
(2) *Inductive electrical loads* usually convert electricity into motion using AC motors. Inductive loads are employed in a variety of home appliances such as refrigerators, vacuums, air conditioners. In this group of loads, there is a phase shift between the voltage and the current (the former waveform lags the latter).
(3) *Capacitive electrical loads* can be considered as the dual of inductive loads, where the voltage peaks after the current sinewave. In a typical household, it is usually assumed that there is no significant capacitive load.
(4) *Non-linear loads* are the ones that the drawn current does not follow a sinusoidal pattern. The major appliances in this group are TV sets, computers, fluorescent lights.
(5) *Composite loads* are the ones in which the device include more than one type of the properties as mentioned earlier. For instance, a refrigerator can be composed of inductive (compressor) and resistive (door lights) loads. In such loads, different load types can operate sequentially, in parallel, or both at the same time [19].

Classification by electrical properties is important to develop mathematical models that represent the load behavior. According to [18], resistive loads can be represented by On-Off models, which includes two states: during *On* state, the load draws fixed power p_{On}, and during *Off* state, zero or some minimal amount of power p_{Off} is drawn.

Similarly, inductive loads can be represented by On-Off decay models with the following parameters: p_{On}, p_{Off}, p_{peak}, and μ. p_{On} and p_{Off} are the same as the *On-Off* model, while p_{peak} shows the level of electrical current when the appliance starts up and μ represents the decay rate to the stable p_{On} level. Suppose that t_{On} represents the length of *On* duration, then the decay model can be represented by,

$$p(t) = \begin{cases} p_{On} + (p_{peak} - p_{On})e^{-\mu t} & 0 \leq t \leq t_{On} \\ p_{Off} & t \geq t_{On} \end{cases}. \tag{1}$$

2.2. Classification by job type

The primary objective of energy management systems is to reduce the electricity generation cost by deferring certain loads to off-peak hours and by optimally adjusting the power drawn from the grid. It is noteworthy to mention that the job priorities are mainly shaped by the customer preferences; hence, the related literature contains different assumptions on load task priority. In the literature, there are three main job types, and the details are given below.

(1) *Inelastic loads* are the ones with the highest priority, as they are essential for maintaining the user's comfort level. Hence, the demand of such loads has to be met immediately and the energy reduction potential of such appliances with shifting/rescheduling is assumed to be very limited [20]. On the other hand, demands of inelastic loads can be coupled with the distributed generation and storage units and the peak hour consumption can be reduced [21]. The appliances considered in this group are lighting, TV, computers, refrigerators, cooking appliances.
(2) *Elastic loads*, on the other hand, are flexible loads that can be deferred and rescheduled to low consumption periods. The deferral period usually depends on the customer preferences and the loads in this group can be further subcategorized into the following. The loads in the first subgroup are *delay sensitive*, meaning that there is a hard deadline to meet the demand, i.e., charging the electric vehicle by 7 a.m. in the morning. The Second group contains the loads with no hard deadline. Hence, they are considered to be *delay tolerant*. For instance, consumers can defer their clothes washing and drying needs until all other essential jobs are completed. Hence, there is a trade-off between reducing the charging cost and potential discomfort of deferring jobs.
(3) *Smart loads* refer to the types of loads which have a controllable/adjustable power consumption pattern. Hence, depending on the energy consumption profile of the household, smart loads can be adjusted to minimize the charging cost. For instance, electric vehicle charging current can be adapted depending on the network conditions [22], or air conditioning system can be controlled within an allowable comfort range to minimize peaks.

2.3. Classification by size

It is possible to classify the BTM systems according to their sizes as SmartHome/SmartBuilding and Microgrid. Despite such grouping, these systems have one critical feature in common: their ability to act as a model citizen with intelligent control. A model citizen can be described as a single entity which behaves as a load or a generator with predictable and acceptable electrical characteristics. For instance, despite having several houses and distributed generators inside, a smart grid's overall behavior may be equivalent to a load which draws constant power. These are discussed individually below.

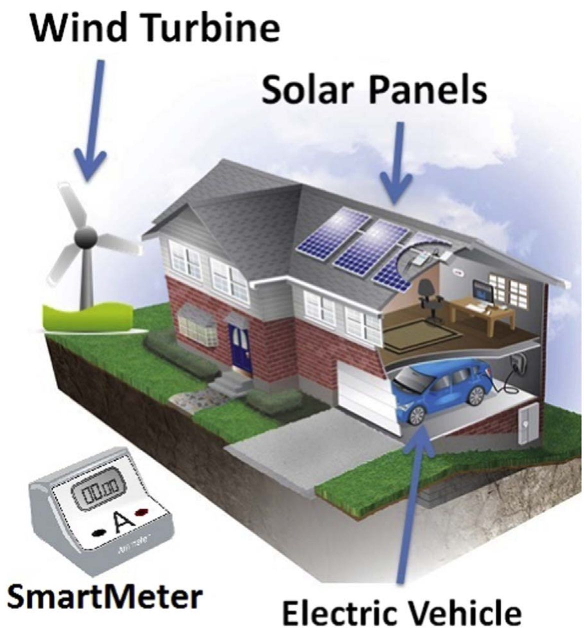

Fig. 8. Smart home design with BTM equipment.

2.3.1. *Smart home/smart building*

This term is used for building (residential or office use) which is equipped with intelligent devices and distributed generators for advanced control. The end-result expected from such control is to maximize internal energy consumption during high demand times. On the other hand, during low demand times, extra energy in a SmartBuilding can be exported to the grid thereby supporting the utility as well as generating income for the building owners.

Fig. 8 shows a typical BTM SmartHome set-up. There are some distributed generators, consumer electronics such as laptops and lighting as well as hybrid devices which can also be used as storage (i.e. electric vehicles). Overall coordination is achieved via a SmartHome interface which can be, at times, SmartMeter itself. SmartHome control can control distributed generator outputs, charge speed of EVs, level and number of loads that are currently served.

2.3.2. *Microgrids*

In this section, a microgrid is used to describe smaller grids which are equipped with smart devices for intelligent command and control.

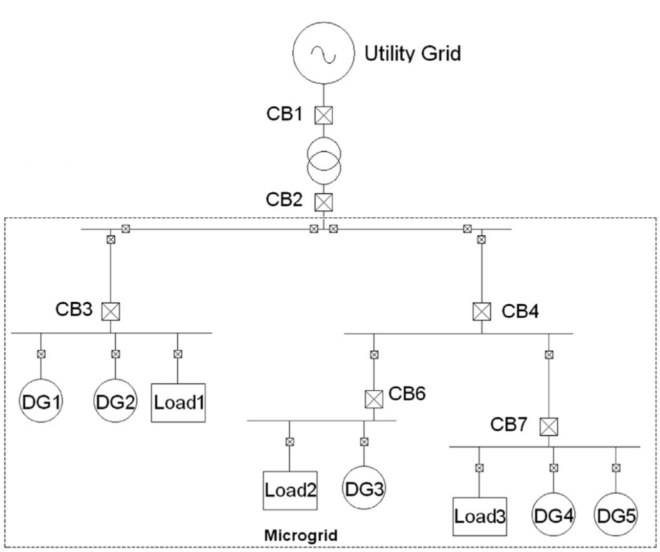

Fig. 9. Microgrid with electrical components.

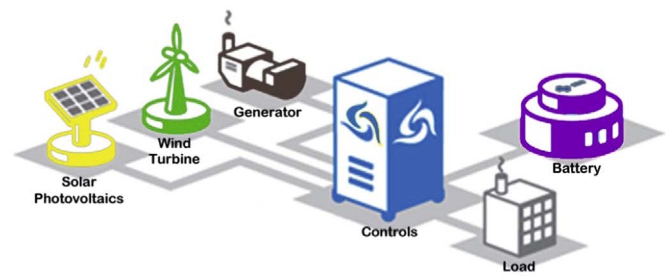

Fig. 10. Smart home design with BTM equipment.

As shown in Fig. 9 below, a microgrid is a collection of loads, distributed generators and equipment required for electrical distribution, protection, and control. In this setup, circuit breaker 2 acts as a point of common coupling (PCC) where microgrid is connected to the utility grid.

A more control-oriented modeling is given in Fig. 10, where the similar devices are represented as lumped models. As known to power engineers, such microgrids are expected to proliferate in near future [23,24]. Therefore, the coupling of such microgrids with the larger utility grid is becoming a necessity.

Understanding the operation of smart microgrids is very easy if a parallel is drawn with the SmartHome concept explained above. Similar to SmartHomes, smart microgrids are controlled so that each one of them acts as a device with acceptable characteristics, such as injected harmonics, caused voltage deviation, etc. With this approach, it is easier to handle the processing load on the entire network, where distributed generators should be taken into account with bulk generation sites. In ideal case, a smart microgrid, may act as a BTM system, PCC can be considered as the meter. Depending on the local generation and consumption patterns, it appears to the utility grid as a load or a generator. Furthermore, the existence of communication lines and intelligent control creates the opportunity for more interaction and planning such as frequency support for the grid.

3. Technology layer

In traditional power system operation and control, the goal is to design a set of rules to match the generation resources with the customer demand, usually with stringent reliability and stability targets. The system is subject to disturbances causing unwanted changes in system state and the control actions are applied to bring back the system to the nominal state. Such operations require continuous monitoring of power system parameters (data acquisition), i.e., line voltage, phase, disturbances, etc., and the control actions take place in microsecond levels. In addition to the load types presented in the previous section, BTM systems have the following primary components: distributed generation resources, distributed energy storage units, and associated control and operation principles. Hence, in this section, we classify such actions in *technology layer* and details are given next.

3.1. *Distributed generation*

Distributed generation (DG) refers to the production of electric power at the point of demand to reduce the cost, complexity, carbon emissions, and inefficiencies of the main grid. Even though there are different definitions for DG systems, the commonly accepted definition states that DG systems are rated less than 10 MW and connected to a voltage less than or equal to 60 kV. The most common generation types include solar photovoltaics (PV), wind turbines, small hydro and wave power, microturbines, diesel generators, and waste-to-energy systems. DG units can be classified into two categories [25]: (1) based on the output, DC or AC; and (2) based on dispatchability. For instance, DG

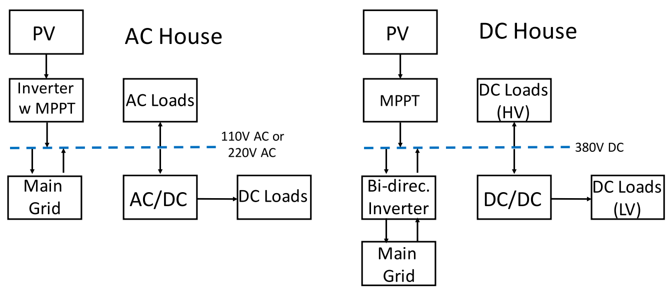

Fig. 11. AC and DC house power system configuration [27].

units such as PV panels and fuel cells are DC-type sources, thus requiring DC/AC power converters. On the other hand, generators like wind turbines and microturbines are AC-type converters, thus require AC/AC converters. For the second classification category, dispatchable generators (e.g., diesel) are the ones whose output can be adequately controlled, while non-dispatchable ones require power electronics tool to extract the maximum available power (e.g., solar, wind) via maximum peak power tracking (MPPT) techniques.

The inverter is a primary component of PV systems, as it affects the performance of the renewable generation. Typically, the efficiency of the inverter technology hovers around 95–98%.[1] However, a sizable portion of the appliances such as consumer electronics including advanced communication technologies, fluorescent lighting, and brushless DC motors operate on Direct Current [27,28]. Therefore, there is an additional need to employ AC/DC power converters, and their efficiencies vary between 85–90% (a typical AC-house configuration is shown on the left side of the Fig. 11). Hence, the system losses could go up to 20% for the DC equipments. Moreover, studies show that replacing AC air-conditioning units with the advanced brushless DC motors can lead to energy savings up to 5–15%, while replacing variable-speed AC motors for applications like water pumping, ventilation, and refrigerators will reduce the energy consumption by 30–50% [27].

As given in the introduction section, there is pressing need to deploy PV panels particularly in the customer premises. Since the output of PV panels is DC and the usage of DC appliances offer significant energy savings, several researchers have evaluated the suitability of DC systems at residential premises [27–29]. Such systems eliminate the need to convert the power from DC to AC and then AC to DC for DC load. The system comparison is shown in Fig. 11. The corresponding energy savings are linked to the PV output, the size and the temporal usage of DC loads. The work presented in [27] evaluates the DC-homes for 14 cities in the US with different load profiles and PV generation profiles. They show that using DC-houses could lead to savings up to 7–8% and the savings could go up to 13% if the household employs an energy storage device.

By far, the most common DG type is photovoltaic systems that have been installed as the solar energy is abundant, accessible, sustainable, and environmentally friendly. Hence, we will focus on the solar generation. One critical parameter to evaluate the PV systems is the breakeven price at which the cost of generating electricity through photovoltaics equals to the cost of purchasing the same amount from the grid. The breakeven price is represented by dollars per watt and depends on factors such as solar irradiance, electricity tariffs, incentives, and the customer load profile. The recent studies conducted by Lawrence Berkeley National Laboratory and National Renewable Energy Laboratory reveal that the price of solar photovoltaic (PV) was reduced by 12–19% in 2013 and the trend continues to fall 3–12% more by the end of 2014 in the United States [30]. Moreover, Department of Energy SunShot Initiative aims to reduce PV integration cost 75% by 2020 [31]. Detailed calculations of cost-benefit analysis can be found at [32] (Table 3).

Similarly, another important driver for the BTM PV penetration is the incentives such as net metering policies which enable end-users to consume the electricity they generate more than their consumption at certain times to offset their consumption from the grid at other occasions. The Database of State Incentives for Renewables and Efficiency (DSIRE) provides details on each State's net metering policies [33]. Australia is also a leading country in BTM solar PV installments. According to the Australian Energy Market Operator, the BTM solar rooftops can meet the one-third of the total demand by 2023 and the trend towards distributed solar generation is expected to grow exponentially as depicted in Fig. 12.

3.2. Distributed storage

Behind the meter storage units are critical technologies as they promote and aid renewable generation penetration. Over the last few years, the political mandates and incentives have boosted the interest in distributed storage units. For instance, California Public Utilities Commission (CPUC) is targeting to procure 1.3. GW of energy storage units by 2020 and 195 MW of this goal will be located at customer premises for BTM energy management applications. Similarly, the U.S. energy storage monitor report [34] shows that, the storage installations increase from 44.2 MW in 2013 to 61.9 MW in 2014, with an increase of 40% in over year. The same report predicts that the deployment pattern will continue to rise with an estimated 220.3 MW total storage capacity. Moreover, almost each state in the U.S. offers incentives for storage units. Just to name a few, the State of California and the State of New York offer $1.62 and $2.1 per watt installed storage units [35]. The increasing deployment pattern in the U.S. is depicted in Fig. 13 and a comprehensive list of policies and incentives can be found at North Carolina Clean Energy Center [33]. Furthermore, the monetary benefits of storage units can be enumerated as:

(1) *Improved power quality* refers to the voltage outages and sags experienced by end-users, which is, in most cases remains unnoticed, but if they occur for a sufficiently large duration, they may damage customers' appliances. Based on a survey study conducted in [36] the average of momentary outage costs for residential customers is 0.10$/kW and 0.42$/kW for small commercial and industrial customers.
(2) *Improved power reliability* refers to the usage of storage units during outages and blackouts. The work in [37] reports that the average 2 h outage cost for residential customers is 3.94$/kW.
(3) *Reduced Time of Use* (*TOU*) *charges* include the monetary savings occurred by eliminating the usage of peak hour electricity, and using storage instead. “Time Of Use” tariffs may vary in different territories and for different seasons.
(4) *Energy Trading* Storage units can also store renewable energy and enable the users to sell it back to the grid to make extra profit.
(5) *Demand charges* is a considerable portion of the commercial and industrial customers' bill. Some electric utilities also apply these charges to residential customers. It is usually computed by the amount and the duration of the peak usage [38]. Demand charges usually apply to commercial and industrial customers. For instance, according to [38] the average demand charge for small commercial and industrial customer is 15.00$/kW.

An overview of current BTM storage projects and commercial products are presented in Table 4.

3.3. Control and operation

Reliable operation of BTM systems requires coordination among the renewable generation sources and the energy storage units. BTM

[1] A detailed list of Inverters approved by California Energy Commission can be found in [26]

Table 3
Classification of load types for behind the meter applications.

	Load type				Priority type							
Load	Restve	Indctve	N-linear	Comb.	Elastic Delay T.	Delay S.	Inelastic	Auto[a]	Manual[a]	Meas. Ref.[c]	Share[b]	EMS[i]
Lighting	✓						✓	✓		[18]	14%	L
Toaster	✓						✓		✓	[18]	2[d]	L
Kettle	✓						✓		✓	[18]		L
Sandwich Maker	✓						✓		✓	[18]		L
Microwave			✓				✓		✓	[18,195]		L
Oven	✓					✓			✓	[18,20,195]		M
Coffee Maker	✓						✓		✓	[18]		L
Refrigerator		✓					✓		✓	[18,195]	8%	M
Freezer		✓					✓		✓	[18,195]	2%	M
Central A/C		✓				✓	✓			[18,20]	18%	H
Dish Washer				✓	✓	✓				[18,20,195]	2%	H
Wash. Machine[1]				✓	✓			✓		[18,20,195]	1%	H
Dryer				✓	✓			✓		[18,20,195]	4%	H
TV[2]			✓				✓		✓	[18]	7%	L
PC[3]			✓				✓		✓	[18]	3%	L
Sp. Heating	✓				✓			✓		[18,20]	6%	H
Wtr Heating		✓							✓	[18,20,195]	9%	H
Other											24%	
EV		✓				✓		✓				H

[a] Refers to the automatically/manually operated appliances.
[b] Aggregated sum of cooking activities (includes all related appliances).
[c] This column refers to the measurement based studies of actual appliances. Different brands are used in measurements, see the references for details.
[d] Based on U.S. residential electricity consumption survey in 2012. Available at U.S. Energy Information Agency [188]. EMS potential classification (H)igh, (M)edium, (L)ow.
[1] It does not include water heating portion.
[2] Includes TVs, set-top boxes, home theater systems, game consoles, and DVD players.
[3] Includes laptops, desktops, monitors, networking equipment.

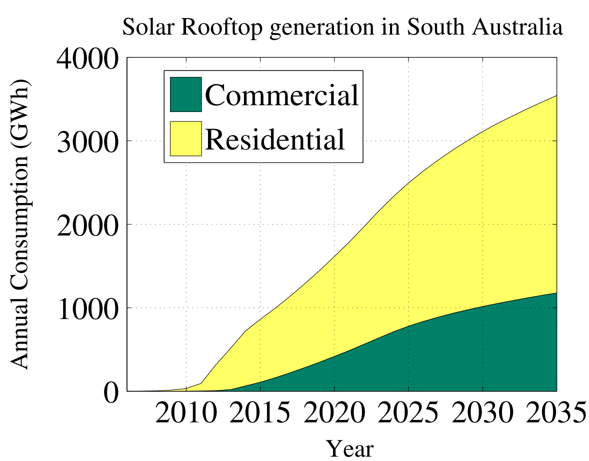

Fig. 12. Solar PV deployment in South Australia [201].

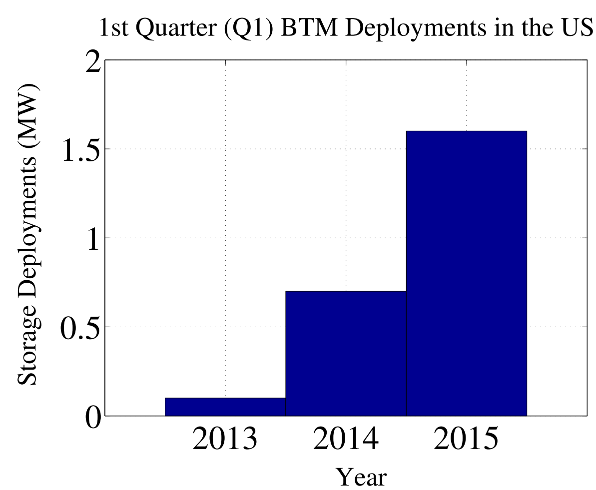

Fig. 13. BTM energy storage deployment in the U.S.

system can operate in the grid-connected mode and stand-alone (islanded) mode with the ability to switch from one mode to another [39]. The main difference between the two operating modes is that in grid-connected mode power exchange between the BTM system and the main grid is allowed through the Point of Common Coupling (PCC). In the stand-alone mode, the generated real and active power should be in balance with the local demand, hence, there is no PCC in this mode of operation [25]. The integration of distributed generation and storage units introduce an array of operational challenges that need to be addressed to enjoy the benefits of the BTM systems. Therefore, the issues arising in the control and operation phases vary and the most common challenges include [25]:

(1) *Stability issues*: There can be local oscillations arising from the interaction of the distributed generation control systems. Therefore, small disturbance stability analysis is required. Moreover, if the BTM system is capable of switching between the grid-connected and islanded modes, transient stability analysis are

Table 4
Behind-the-meter system deployments.

State	**Details**
California	CPUC has provided incentives to 6.8 MW BTM storage units.
Arizona	Arizona Public Service to deploy 2 MW of distributed storage and solar.
Illinois	ComEd to invest $300 million for microgrid projects.
New York	2 MW behind-the-meter storage contracted by Con Edison.
New Jersey	Board of Public Utilities has awarded $2.9 million storage projects.
Texas	ERCOT provides incentives for utility-controlled distributed storage units.
Commercial products	ZBB [196], Gexpro [197], Tesla [198], SolarWatt [199].

Table 5
Literature Analysis on Optimization.

	Load types			Objective						
Refs.	Wet appl.	HVAC	EV	Elec. cost	PAR	Loss Mn.	Comfort	Target cur.	Soc. welf.	GHG
[85,86]		✓		✓						
[87–89]	✓	✓		✓						
[53]	✓	✓		✓	✓					
[91]	✓	✓		✓			✓			
[22]			✓	✓		✓				
[47]	✓	✓		✓			✓			
[49]	✓	✓	✓	✓			✓			
[50]	✓	✓	✓	✓					✓	
[51]	✓	✓		✓	✓					
[82,83]			✓	✓						✓
[69,71]	✓					✓		✓		

crucial for seamless transitions.

(2) *Bidirectional power flows*: Traditional distribution feeders are designed for unidirectional power flow. Hence, in the grid-connected operation mode reserve power transfers can lead to complications in the protection of the system.

(3) *Uncertainty*: The high uncertainty associated with the load profiles and renewable generation units poses challenges in reliable operation of BTM systems. The uncertainty is a bigger problem in islanded mode of operation, as the supply-demand balance is affected by high component failure rates.

(4) *Low inertia*: As the BTM systems expected to employ a low number of distributed generators, low-inertia characteristics, which can lead to frequency deviations, are likely to be experienced.

In order to attack the issues given above, the BTM system controller should be able to (1) control the output of the generation units, (2) ensure power balance and keep voltage and frequency deviations within predefined standards, (3) adjust and shift some portion of the loads (smart and/or flexible loads), and (4) switch between the two operation modes if required. Therefore, the primary control variables are voltage, frequency, and active/reactive power (Table 5).

The control techniques can be classified into two groups: centralized and decentralized control. In the first one, a central controller gathers data from all units and decides control action for the entire system. In decentralized control systems, decisions are taken at each control unit with the available local information. In typical BTM systems, hybrid models are used because (1) central control units require extensive data communications and (2) decentralized controller may fail to stabilize the system as there is a strong coupling between physically dispersed generation units. Such hierarchical control techniques typically have three control layers: (1) primary, (2) secondary, and (3) tertiary. Three control levels are differentiated according to their response time; primary control being the fastest and tertiary control has the slowest response time. Moreover, primary control is employed at single power electronics level, while secondary control is responsible for a group of distributed generators, and tertiary control level is responsible for a group of interacting BTM systems. Next, we provide details on each control level.

3.3.1. Primary control

Primary control uses only local information. Hence, it has the fastest response time. The control techniques in this category include power sharing, inverter output control and islanding detection [39]. In power sharing, the goal of the control action is to adequate share of active and reactive power imbalances, which if not controlled leads to frequency deviations [40]. The most common power sharing techniques are divided into two [39,40]: (1) droop-based [41,42] and (2) non-droop-based techniques [43,44] and a detailed comparison can be found in [25].

The control of the inverter output has been extensively discussed in the literature [25,45,46]. Overall, controllers in this category are classified into three with respect to their reference frame. The first one is the synchronous reference frame, which is related to DC variables and Proportional Integral (PI) controllers. The second reference frame is called stationary frame and it is linked to sinusoidal variables and Proportional Resonant (PR) controllers. The last group is the natural reference frame which employs PI, PR, and hysteresis based controllers.

3.3.2. Secondary control

Secondary control techniques aim to provide secure, reliable, and economical operations. This task is more challenging in islanding mode because the unit dispatch of the highly variable energy resources should follow sudden changes in the demand. The secondary control is the highest level in the islanding-mode and it operates in a slower time frame as performing complex decisions takes more time. Also, secondary control handles economic dispatch of generation and storage units [25].

There are two main secondary control approaches. The first one is the centralized approach, in which a central operation point gathers all relevant information and performs online optimization routines. The second method is decentralized, which takes optimization decisions in a distributed manner. Overall, centralized approaches are suitable for BTM systems operating in stand-alone mode, as this system often experience supple-demand mismatch. On the other hand, distributed approaches are more appropriate for grid-connected BTM systems [25].

3.3.3. Tertiary control

Tertiary control is the highest level in the control hierarchy and it only exists in the grid-connected mode. The main objective of tertiary control is to coordinate multiple BTM systems and the main grid. This control level is the slowest compared with the other two levels (typically in the order of minutes). The main reason is that the signaling between the secondary level and the time to take control actions take time. Typically, tertiary control is considered to be part of the main grid [25].

4. Economic layer

The conventional power system operations have been successful in terms of grid stability and reliability, but the principle of matching the resources to the customer load leads to underutilized assets. Moreover, with the deployment of distributed generation and storage technologies, the power grid operations become more complicated and costly, and hence new tools are required to maintain demand-supply match. Considering the fact that the user behavior has an enormous impact on how the network is utilized, many aspects of the power grids are

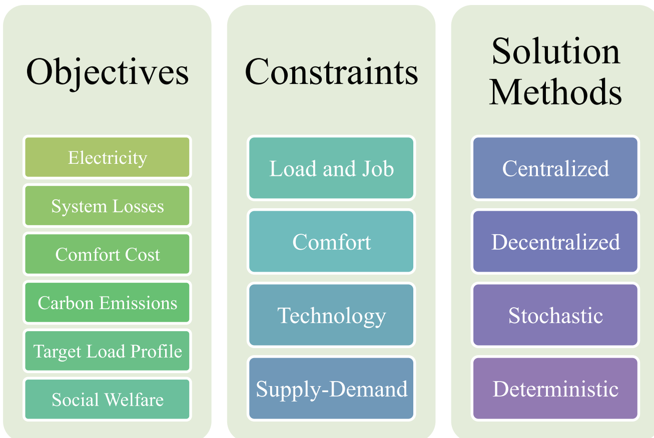

Fig. 14. Economic layer components.

governed by the economic incentives than by technology layer presented in the previous section. Hence, one effective way to shape the load profile is through *economic incentives* to optimize and schedule customer demand both in time and quantity. In such problems, the idea is to minimize a cost function (or maximize benefits) that is usually subject to several technological and economic constraints. The methods that are presented next constitute the *economic layer* and an overview of this section is presented in Fig. 14.

4.1. Objective functions

The main thrust of an energy management system is to reduce the power grid operation cost while maintaining a good level of customer comfort. The major components of such costs are represented by following objective functions: (i) electricity cost; (ii) distribution system loses; (iii) customer comfort cost; (iv) carbon emission related costs; (v) reaching a target load profile; and (vi) social welfare. It is noteworthy that, the optimization problems are usually represented by utility functions that may have one or more of the enumerated objectives. Next, we present the details of the optimization objectives, the constraints, and the solution methods.

4.1.1. Electricity cost

Electricity cost is the first major component of the cost function. The electricity price is usually considered as an exogenous variable given by the utility, which depends partially or entirely on varying the retail prices. The works presented in [21,47–50] employ real-time electricity prices in their objective functions and the goal is to minimize the total consumption cost.

4.1.2. Peak-to-average load ratio minimization

The peak-to-average load ratio is a way of measuring the efficient utilization of the grid resources. For instance, if this ratio is close to one, the load profile is almost flat and the resources are highly utilized. On the other hand, if this ratio is low, then there is a significant unused system capacity, which translates into higher operational cost. Over the last two decades, peak-to-average demand ratio has been steadily increasing in the U.S., which translates into reducing utilization of grid assets and increasing power grid operations. Hence, series of papers propose methodologies to reduce the peak-to-average load ratio through energy management systems [51–54] and [55].

4.1.3. Energy loss minimization

During the delivery of the power from the central power plants to the end-use site, some portion of the electricity is lost, mostly in the form of heat due to the resistance of the lines and other equipments that the electricity passes through. For instance, according to the U.S. Energy Information Administration, 6.1% of the net electricity generation was lost in T & D network. By considering the average electricity price, this accounts approximately for $19.5 billion. Similarly, energy losses at house level are documented in [56] for EU countries. To that end, several literature on energy management systems focused on minimizing the energy loss by deploying distributed generation options. Since reducing losses is related to using local production, the majority of the studies in this area aims to find the optimal dispatch strategy [22,56–59]. For instance, authors in [22] propose an optimization problem to minimize the energy losses for electric vehicle charging. Similarly, authors of [58] develop an intelligent scheme to minimize the energy losses to improve voltage profile. In [59], authors propose aim to reduce the distribution system losses.

4.1.4. Customer comfort

Even though energy management systems offer a wide range of energy savings options, consumers are likely to face with conflicting decisions between the cost and user comfort. Therefore, minimizing the customer discomfort or keeping the comfort within a certain range is one of the important objectives of BTM systems. In [60], authors develop a control framework considering the discomfort experienced by users. The weight of the discomfort component increases in studies that consider the management of cooling units or water heaters, as the usage of such appliances is highly coupled with user comfort [61–68]. The discomfort cost is usually modeled with piece-wise linear function. For instance, if the temperature of the house is within an allowable interval that is bounded some upper and lower thresholds (22 °C ± 4 °C), then the cost increases as the linearly within this range. On the other hand, a huge penalty is incurred in representing the discomfort cost. Furthermore, the study in [49] couples charging electric vehicles with home energy scheduling to jointly minimize the charging cost and maximize the user comfort.

4.1.5. Target load curve

The peak hour power system operation cost are incurred due to stochasticities involved with the human activity. Hence, another profound optimization objective is to incentivize customers to achieve a particular load profile that is suitable for the utility [69–74]. For instance, the work presented in [74] proposes a bidding strategy for a user so that a target load profile can be achieved. On the other hand, this approach requires consumers to reveal their usage profile so that energy management system can compute optimal scheduling policy for each appliance, which may not be the case in an actual implementation of the system. This approach is also employed for energy management in electric vehicle charging stations, where the goal is to keep aggregated customer demand below a certain bound with statistical guarantees [75–78].

4.1.6. Social welfare maximization

Social welfare (or social surplus) represents the sum of all consumers' net benefits, i.e. the sum of aforementioned benefits minus the associated costs. Hence, the primary objective is to be able to solve individual energy management problems in such a way that the social welfare is maximized in the global scale (through all consumers). For instance the works in [50,66,79–81] present energy management formulation to maximize the social welfare.

4.1.7. GHG emission minimization

The last objective of the energy management systems is to reduce the GHG emissions related to electricity generation mainly by increasing the utilization of clean energy options. For instance, the work in [82] presents an optimization framework to reduce carbon emissions in the presence of renewable generation. In [83], authors aim to minimize the carbon emissions resulting from electricity generation in a group of buildings.

4.2. Constraints

The formulation of energy management problems is usually subject to one or more constraints that are explained as below.

(1) *Load constraints* determine the lower and the upper bound power consumption level (e.g., appliance i $p_i^{min}(t) \leq p_i(t) \leq p_i^{max}, \forall t$). For instance, clothes dryer or electric vehicle can reduce its consumption to aid critical loads. These loads are usually considered as *smart loads* as they improve energy management capabilities.
(2) *Comfort constraints* capture the occurred inconveniences due to deferred/scheduled loads. It is noteworthy that comfort preferences could both be a constraint and an objective function.
(3) *Storage unit constraints* are an important set of technological limitations that the management systems are subject to (e.g., energy and power rating, efficiency, etc.).
(4) *Job constraints* represent the priority of the jobs. High priority loads are usually delay sensitive and have very stringent deadlines while low priority loads can have loose delay constraints. The performance metric could either be individual deadlines or the average delay constraint for all jobs.
(5) *Distributed generation constraints*, similar to storage limitations, are technical restrictions that determine that amount of generated power, which is usually a probabilistic variable.
(6) If the available generation is scarce (e.g., coupling deferrable loads with renewables [84]), then another significant constraint is the *supply-demand match*. The energy management scheme must make sure that supply meets demand at all times.

4.3. Solution methods

The solution method of an optimization problem depends on the assumptions of the decision maker and the properties of the objective functions and the constraints. There are two main assumptions on policy makers. In the first one, a *central* authority such as utility operator, dictates the schedule of appliance operations aiming to maximize the system-wide objective function. In the second strategy, on the other hand, individuals take their own decisions and the goal is to maximize individual goals. Hence, the problem is solved in a *distributed* manner.

The existing works in the literature are further classified into two groups. The first one is related whether the problem is solved at *one-shot* or the problem is transformed into a sequence of simpler problems and solved in *multi-stages*. For instance, users can schedule their appliance usage at the beginning of the day or the same procedure can be updated every 15 min depending on varying conditions (e.g., prices, renewable generation etc.). The second classification parameter includes whether the problem contains random variables to represent the uncertainty introduced by the decision variables or the constraints. Such problems are referred as *stochastic programming* the goal is to maximize the expected outcome. On the other hand, if all parameters are known with certainty, then this group of problems falls into *deterministic programming*. Overview of the classification methods is presented in Fig. 15.

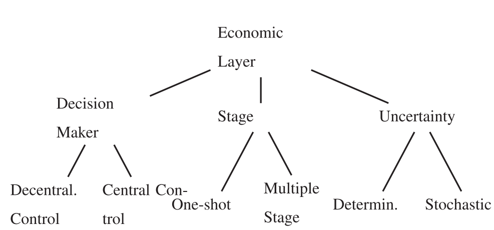

Fig. 15. Classification of optimization problems.

4.3.1. Centralized solutions

The most common centralized solution method is direct load control (DLC), which is a contract between the utility and the customers. According to this agreement, the utility may control the operations of residential appliances during critical times. In such strategies, the goal is to maximize a single objective function and solution method depends on the properties of the functions. Depending on the structure of the energy management system, the problem formulation falls into the groups given below.

(1) *Linear programming* (LP) is a type of optimization problem where the objective function and all of the constraints are linear and deterministic. The optimization problem can be solved with well-established algorithms such as simplex, revised simplex, or interior point method. The works presented in [85–88] and [89] employs LP in their energy management problem. Since there is no uncertainty in LP problem formulations, such approaches fail to capture distributed generation dynamics and price and demand uncertainty.
(2) *Heuristic optimization* is a powerful tool to solve intractable problems that usually include uncertainty by nature [90]. In heuristic optimization, there is no need to have global properties of the objective functions and its derivatives. For instance, *genetic algorithm* (GA) is a widely used method in heuristic optimization that use mechanisms inspired from the evaluation of biological processes (e.g., natural genetics and selection) and computes the optimal value by searching through the solution space. The works presented in [53,61,91] employs such an optimization method. The work presented in [92] employs *particle swarm optimization*, which is an iterative search algorithm that aims to improve the candidate solution in a search-space following a simple predefined set of rules. Heuristic optimization can also be used to solve Mixed Integer Linear Programming (MILP) problems, which arise if some of the objective or the constraints are integers. For instance, branch and bound search algorithms are used solve the problems presented [93–96]. This can also be applied when the problem is non-linear. The work presented in [57] formulates the energy losses minimization problem with mixed integer nonlinear programming (MINLP) and aims to find the best generation portfolio. Moreover, the study in [96] proposes an energy management controller aiming to minimize electricity bill while considering the comfort level. The problem is MINLP and the solved by iterative algorithms.
(3) *Convex optimization* problems include convex objectives and constraints. Mathematically, convex optimization problem is defined as $\min_x f_0(x)$ subject to $f_i(x) \geq b_i, i = 1, \ldots, m.$ and $f_0, \ldots, f_m: \mathbb{R}^n \to \mathbb{R}$. If the problem includes convex functions, thanks to recent improvements in optimization and computing theory, the solution is as straightforward as linear programming. Some solution methods include least squares, conic programming, Lagrange multiple methods, geometric optimization [97]. For instance, the works presented in [51,98] employs convex optimization methods.
(4) *Dynamic programming* is a powerful optimization technique that structures the problem in multiple stages, and the problem is solved one stage sequentially at a time. Usually, customer energy demand is time-correlated, meaning that energy requirements and constraints (e.g., comfort level) vary over time. In such cases, energy management problem cannot be optimized independently at each time interval. Hence, dynamic programming approaches are heavily employed. For instance, Markov decision process can be applied to solve dynamic programming problems in which the goal is to find a policy that maximizes the *rewards* of the actions taken at each step. The necessary condition for optimality of such problems is associated with the *Bellman's principle of optimality* equation [99]. The works presented in [100] and [101] uses

dynamic programming for energy management systems.

(5) *Stochastic optimization* problems are mostly used to capture the uncertainties introduced by energy management system components like renewable resources, electricity prices, and human activity. In general, stochastic optimization can be used to represent both *one-shot* or *multi-stage* problems. Since the latter one is predominantly used, we focus on the multi-stage decision-making case. In stochastic optimization problems, the system is represented by a probabilistic scenario tree that represents the available steps at each time (similar to dynamic programming). However, the state of the scheduling tree increases exponentially at each time slot, hence *multi-stage* stochastic optimization can suffer from the *curse of dimensionality*. To overcome this issue, two-stage stochastic programming approach is used in which decisions are taken based on the available data, and they do not depend on future observations [102]. Other powerful techniques to solve stochastic problems are *Markov decision process* (MDP), *Lyapunov optimization*, and *model predictive control* (MPC). Overall, the goal is to find a policy that performs well on average while it is feasible for all parameters. For instance, the studies in [103,104] use MDP to solve the stochastic optimization problems. Furthermore, the works presented in [21,105,106] use Lyapunov optimization models, while the works in [49,107–109] use MPC for residential energy management systems.

4.3.2. Decentralized solutions

The aforementioned centralized optimization methods can be powerful, however, such approaches raise concerns about consumers' privacy and comfort, as the centralized methods require complete knowledge of the appliance usage. As an alternative to direct load control decentralized control techniques that do not violate user privacy and comfort, as individual users take their decisions to maximize the aforementioned objectives. One effective way of such schemes is the *smart pricing* methods provide consumers economic incentives to influence their electricity consumption.

4.3.3. Smart pricing

Over the last decade, the differentiated pricing schemes have become popular. In such schemes, utilities compute electricity tariffs for different periods of the day to shape the consumer demand profile. Next, we elaborate the details of the pricing schemes employed in the literature and an illustrative example is presented in Fig. 16.

(1) *All-in-rate* refers to static electricity rates that remain unchanged throughout the day. It is calculated as follows. First, utilities compute the cost of electricity for different consumption levels and then, by further considering the length of such intervals, the weighted average cost for one day is calculated. In the final step, the electricity delivery cost and the basic charge is added on top of the average cost of electricity. For instance, there are five tiers in California, namely, (Baseline) $\times$ {(0 − 100)%, (101 − 130)%, (131 − 200)%, (201 − 300)%, %(301 − above}, with a unit cost of {0.045,0.065,0.151,0.186,0.221}\$/kWh respectively. According to [110], the average price becomes \$0.092/kWh and this cost is added to the average delivery cost (\$0.072/kWh) and the basic charge (\$0.020/day), and the all-in summer electricity cost is calculated as \$0.165/kWh.

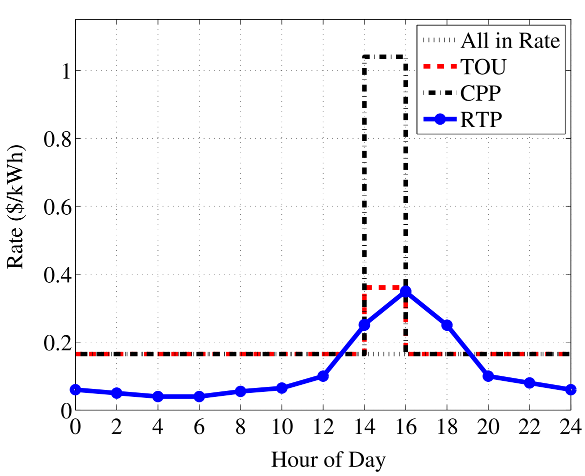

Fig. 16. Comparison of smart pricing schemes.

(2) *Time-of-Use* (*TOU*) *rates*, typically divide the days into several periods (e.g., peak, mid-peak, peak, etc.) and compute a rate for each period. Such periods, hence the prices, depend on the season (e.g., spring vs. summer), the day of the week (e.g., weekends, weekdays, etc.). TOU rates are held constant throughout every period. Therefore, they do not fall into dynamic prices. The very first step in designing the TOU is to set the off-peak electricity price to utility's marginal cost. Then the peak hour rate is computed to be revenue-neutral to the all-in-rate by considering the average residential load profile. In California, summer season off-peak and peak hour prices are ¢12.6/kW h and ¢36.1/kW h respectively [110]. More rates for other states can be found in [111].

(3) *Critical-Peak Pricing* (*CPP*) rates are usually employed with TOU rates, meaning that during critically loaded periods, customers pay a peak rate that is higher than any other rate. During the rest of the times, CPP acts exactly as TOU pricing. In order to compute the residential critical-peak price, utilities consider the cost of a typical combustion turbine and de-rate this cost by 30% since there is a cost associated with the uncertainties of time the of the dispatch and the availability of the rate. Next, the de-rated amount is divided by the number of critically loaded hours, and in the final step the result is added to the existing all-in rate critical rate. A simple example will clarify the matters. A typical cost of a combustion engine in California is \$75/kW-year and the all-in-rate for summer is ¢16.5/kW h. Considering 100 h of critical load during a typical summer season, the corresponding critical-peak rate would be $\$75 \times 0.7 \div 100 + ¢16.5 = \$1.04$/kW h.

(4) *Real-Time Pricing* (*RTP*) refers to the tariffs that are computed either hourly basis and this information is delivered to end-users either on hour-ahead or day-ahead basis. For instance, in the State of Illinois two utility companies employ such programs. Customers of Ameren Illinois, who are enrolled in “Power Smart Pricing” program, receive hourly prices that are set the night before, and they adjust their usage accordingly [112]. Another Illinois utility company Commonwealth Edison (ComEd), on the other hand, offers an RTP program and broadcasts their prices hour-ahead [113]. The computation of RTP for ComEd is calculated according to the following formula. $p_d(h) = P_{DA} + C_D - PI$, where $p_d(h)$ is the electricity price at hour h on day d, P_{DA} s the day-ahead wholesale market price, C_D is the distribution cost (¢5.0/kW h), and PI is the participation incentive (¢1.4/kW h) [114].

(5) *Inclining block rates* (IBR) is a powerful pricing mechanism to avoid peak demand. Under this rate structure, the unit price of electricity increases with the usage in blocks of several hundred kWh. Hence, this provides incentives to distribute the usage over time. According to [115], the prices are {0.0469, 0.0502, 0.0621, 0.0717} ¢/kW h for the consumption blocks of {(0–50), (52–350), (351–600), (600-above)}, respectively. The works presented in [47,53,55] use IBR in their optimization schemes and the work in [116] discusses the results of an implementation in Canada.

4.3.4. Game-theoretic approaches

Even though smart pricing schemes have been on the market for many years, according to a measurement-based study in [117], if employed alone, they provide limited energy shaping capabilities. The main reason is that customers do not likely to follow price variations and manually adjust their appliances. Also, individual customer usage should be harmonized in order to improve the savings. To that end, recent studies [118,119] and [51] show that instead of considering only on the individuals, i.e. smart pricing, direct load control, developing an energy management system for a set of users leads to better savings, mainly by allowing consumers to adjust and coordinate their usage.

Hence, we proceed to explain distributed control techniques, which employ game theoretic tools to model and study the complex interactions among the independent rational player. A game $\mathcal{G}$ is defined in its strategic form as $\mathcal{G} = \{\{\mathcal{N}, \{X_{i\in\mathcal{N}}\}, \{U_{i\in\mathcal{N}}\}\}$. In game theory, each player $i \in \mathcal{N}$ chooses a strategy $x_i \in \mathcal{X}_i$ to maximize his/her utility function (payoff) $U_i(x_i, \mathbf{x}_{-i})$, which depends both on his/her strategy x_i and all other players' strategies $\mathbf{x}_{-i}$.

The player setting can be single user – single utility, multiple users – single utility, or multiple users – multiple utilities. Furthermore, games can be classified into two main branches: cooperative games and non-cooperative games. Next, we provide more details on the modeling and solution methods presented in the literature.

(1) In *cooperative games*, players (e.g., customers) can communicate with each other so that the entire group of users can act as one super entity to further reduce the energy consumption. For instance, the work presented in [69] propose a cooperative game between users in order to achieve the desired load profile that is suitable for grid conditions and utility company. They show that as people cooperate, the cost of electricity consumption further reduces. In [120], authors propose cooperative and coalition game to in a group of energy users to minimize their usage. A similar methodology is applied in [119,121,122]. A common objective of the group of users is to maximize the social welfare [123,124]. In this type of approaches, when users reach their optimal usage, they do not have any incentive to move from this point. Hence, these set of points leads to *nash equilibrium*.
(2) *Non-cooperative games* examine decision-making processes of a self-interested set of consumers who do not have any communication with each other. In several cases, there can be cooperation among customers due to self-enforcing reasons. The non-cooperative game theory has been extensively used in the literature, as there is usually a conflict between the consumers in terms of maximizing the comfort level while aiming to maintain a certain degree of comfort. The works fall into this group contain [80,125–129]. For instance, the work in [80] proposes an aggregative game for selfish consumers to manage the energy consumption behavior of users. They show the existence Nash equilibrium. Moreover, the work in [125], proposes a stochastic differential game-based energy management system with smart/controllable loads e.g., water heater, A/C, etc.

5. Social layer

The fundamental shift towards the smart grids requires customer engagement, which has been ignored for many years. According to the U.S. Department of Energy, the role of consumer preferences, choices, and behavior is as important as technical requirements [130]. The literature in psychology and sociology shows that moral payoffs and moral norms have a significant impact of the household energy consumption [131]. Therefore, the main premise of employing social sciences in energy studies is to shape the energy consumption and achieve reasonable carbon emission reductions without requiring any technological upgrades *behave*.

The successful deployment of EMS is ultimately related to modeling and understanding of the actual consumption patterns, which depend on socio-economic factors, dwelling related factors, and appliance-related factors [19,132,133]. According to the study conducted in [19], there are 13 socio-economic, 12 dwelling-related, and 37 appliance-related existing factors. Obviously, only a few of them are dominant in the domestic electricity use. For instance, [133] states that age, the number of residents and employment status are the most influential parameters in Belgium. Next, we span some of the most important factors that affect and determine the domestic electricity consumption. Then, we will show the recent literature on social studies that use these elements to reduce energy consumption and promote energy conservation. In Fig. 17, we present the overview of social layer components.

Fig. 17. Social layer components.

5.1. Socio-economic factors

The widely accepted socio-economic factors on domestic electricity consumption are listed below.

(1) *Active occupancy* refers the number of people, who are using the appliances. This number is likely to vary during the day. The relationship between active occupancy and the domestic electricity usage has been extensively studied in the literature and the common conclusion reveals that there is a significant positive correlation between them [134–138]. A comprehensive overview is presented in [19].
(2) *Household income* is another strong determinant of the energy consumption. From microeconomics, it is known that electricity consumption per capita (kWh per person) is highly correlated with household income that determines the comfort level. Similarly, series of studies [134,136,137,139] have concluded that electricity usage increases as the household income grows. For instance, according to [140] top 1% of the households with high income consume four times more electricity than the average user.
(3) *Age of residents and family composition* also play a useful role in the energy consumption. For example, authors in [135] shows that if the responsible household person is above 55 or between 19 and 50, the electricity consumption is likely to be less than other age groups. The impact of family structure, the number of kids and their ages, depends on the society. For instance, in Denmark and Belgium, consumption reduces corollary with the number of infants/toddlers; however the opposite is true for Portugal [19].

5.1.1. Dwelling factors

There has been an increasing body of literature on investigating the effects of dwelling's physical structure on domestic electricity usage. Very detailed analysis can be found in residential energy consumption survey conducted U.S. Energy Information Administration [141]. The primary factors are enumerated as below.

(1) *Total floor area* is the most significant factor in this group, as it determines the demand for space cooling/heating, the number of appliances and occupants, etc. up to an important extent [19,142].

For instance, in the U.S. 85% of the new homes built in the last two decade employ central A/C units and this trend has lead to a dramatic increase in energy consumption. Also, in the US according to [140] an average-sized household, that is 1600 square feet, consumes around 9500 kW h/year, whereas top the largest 1% of the homes, that is 6400 square feet, consumes 2.5 time as much electricity.

(2) *Dwelling age* is an important criterion in domestic electric power consumption. According to the analysis presented in [141], although dwellings built in year 2000 and later are 30% larger than the ones built before that date, these homes consume only 2% more electricity than the older ones. This is due to better insulation, improved efficiency of appliances such as air conditioning, lighting, etc.

(3) *Dwelling type* also determines the electricity consumption because the degree of detachment determines the energy savings especially due to space heating [19]. Multi-dwelling apartments are usually more energy efficient than the detached houses [134–136].

5.1.2. Appliance factors

Appliance level factors are also of paramount importance as they determine the significant portion of the electricity consumption. The major ones are listed as below.

(1) *Appliance ownership* is an important determinant of the aggregated consumption. This category can be further divided into subgroups such as total number of ownership (wet appliances, entertainment sets, HVAC, electric vehicle ownership etc.), power demand and efficiency of such devices, and the frequency of usage [19].

(2) *Appliance usage* refers to the daily activity patterns and the frequency of appliance usage. Therefore, appliance usage is an influential element that shapes the peak usage.

(3) *Power demand and efficiency* of appliances are also crucial factors, as, for instance, certified energy efficient appliances consumes less power compared to older appliances. Moreover, weather is one of the most critical factors affecting electricity consumption. In most parts of the world, the highest electricity demands occur in the summer time as end-users increase their air conditioning use to deal with the high temperatures and humidity.

5.1.3. Psychological factors

Another important but often-neglected factors affecting the energy consumption are the psychological drivers. Some of such factors include value priorities, personal norms, self-efficacy, outcome expectations, and attitudes [143]. For instance, the work in [144] shows that the *motivation to save energy* is related to attitudes towards saving energy. Moreover [143] suggests that the effort required to save energy is proportional to the perceived private benefits. Moreover, social norms and self-expectations are the other two important driving factors. Next, we present the recent social studies that shape the end user energy consumption.

5.2. Integrating social sciences

The previous two layers of energy management systems require costly system upgrades and complex system architectures. However, the majority of the time electrical appliances will be used by end-users. To that end there has been a recently growing body of literature in integrating social sciences into the picture [130,143–147].

The work presented in [147] uses behavioral approach to estimate the national reasonable achievable emissions reductions. They categorized different household actions into 5 groups, namely weatherization, *efficient equipment*, *equipment maintenance*, *equipment adjustments*, and *daily user behavior*, that can help to reduce the household energy consumption by 20%.

The work in [143] presents a social cognitive approach to energy savings. They employ the tools given in Section 5.1.3, and conclude that in order to boost the savings through behavioral approach, utilities need to improve the feedback about user's electricity consumption, social market norms, and communicate social expectations.

Moreover, according to [148], peer pressure is one of the most effective methods of reducing electricity consumption. An application in California tries to motivate customers to reduce their consumption by comparing the individual bills with the average consumption of their neighbors. This method enables customers to reduce their consumption by 1.5–3.5%.

The behavioral theory could also become a powerful tool in energy conservation. For instance, the work presented in [131], researchers provide a health and environment-based messaging strategy to lower the energy consumption in the homes. The study shows that health and environment-based information lead to 8% of energy conservation.

6. Enabling technologies

The successful deployment of BTM energy management systems requires enabling communication, sensing, and control technologies to ensure timely information dissemination. Overall, the communication networks for the smart grid can be divided into three categories, namely Home Area Network (HAN), Neighborhood Area Network (NAN), and Wide Area Network (WAN) [149]. HAN usually consists of tens of appliances in the customer premises for BTM energy management applications. Usually, HAN contains a central controller, which is connected to a smart meter to interface with the power grid. NAN, on the other hand, aggregates data from multiple NANs, which typically represents a few hundred meters, and forwards a data concentrator. WAN delivers the aggregated information from NANs to the utility company to take central decisions on pricing, load control, forecasting, etc. Since BTM systems can be a single house and group houses owned by a single entity, both HAN and NAN technologies are considered in this study. A detailed survey of communication technologies and protocols for smart meter (automatic meter reading) applications can be found in [150] and more general communication survey can be found in [151].

6.1. Communication technologies for customer premises

Suitable communication technologies for HAN applications can be classified into two categories based on the communications media. The first group of technologies uses wired media and the candidate technologies include Power Line Communications (PLC), and Ethernet. The second group, on the other hand, uses wireless media for communications and The most common communication technologies are IEEE 802.15.4 based technologies (e.g., ZigBee) and Wi-Fi. The advantage of the first group is that these technologies can provide fast and more robust communication medium. However, wireless communications can provide low-cost infrastructure and ease of connection to unreachable areas.

6.1.1. Wired communications

• *Power line communications* (PLC) use the existing powerlines as a communication medium to transmit information between appliances and the energy management unit. Depending on the used frequency band and the data rate, PLC technologies can transmit up to 4–10 Mbps. The advantage of PLC is that the deployment cost is comparable with its wireless counterparts. On the other hand, the main disadvantage is the harsh and noisy channel environment. In order to support usage of PLC and to provide a standard, HomePlug Alliance has been established to provide affordable smart grid solutions. To that end, the work in [152] proposes a channel model for indoor PLC. Moreover, the works presented in [153] and [154] uses PLC as a communication technology for energy management systems.

A detailed analysis of the PLC can be found in [155].

• *Ethernet* communications is another possible, but less preferred communication option. Even though it can provide very reliable and fast communication medium, the physical cabling and the related cost becomes an obstacle.

6.1.2. Wireless communications

• *IEEE 802.15.4* standard defines physical layer and media access layer specifications for low-rate wireless personal area networks. Since the sensing and the monitoring devices run for long duration and requires low bit rate technologies, IEEE 802.15.4 based technologies are widely accepted in energy management applications. *Zigbee* is the most popular and suitable wireless communication technology for energy management systems due to its simplicity, mobility support, low deployment cost, its usage of unlicensed spectrum [17]. In fact, many smart meter vendors, i.e., Itron, Elster, etc. and major home appliance manufacturers, i.e., General Electric, LG, etc., have started to embed ZigBee in their products. To that end, there has been a growing body of literature on the use of ZigBee in energy management systems [156–159]. The technical details of Zigbee can be found in [160].

• *Wi-Fi* based *Wireless Mesh Networks* (WMNs) can also provide required connectivity and data transfer for energy management applications. WMNs could play a critical role if the generation, storage, and the loads are physically separated in distance, which is the case for microgrids and campus networks, and thus requires wider area network coverage. Moreover, WMNs are highly scalable, self-organizing, and their low implementation cost makes them a good option [17,151].

• *Femto cells* are often deployed as access points of cellular networks. Femtocells use customer's broadband, DSL, or any other related technology to connect to the wireless carrier's core network. This way, femtocells offer required indoor coverage and capacity for BTM energy management systems. Femtocell also employs mature security systems and the details are given in [161].

• *Wireless Wide are Networks* could provide required connectivity to BTM energy management systems if it is located in a wider region such as a microgrid or a campus [14,15,162]. The main advantage is that customers can use public cellular carriers and there is no need to built a communications infrastructure. On the other hand, since the existing networks are not built for a machine to machine communications, hence modifications might be required. On strong candidate technology is Worldwide interoperability for microwave access (WiMAX). WiMAX can provide high capacity, wide coverage, low latency, low per-bit cost, and required quality of service capabilities.

6.2. Communication technologies for distributed energy generation

Communication systems are the essential components for the integration of distributed generation assets. Applications such as supervisory control and data acquisition (SCADA), protective relaying and feeder automation are crucial for the proper operation of system [163].

6.2.1. Communication systems for wind generation

Communication of measured information and control signals between the small scale wind generators and the central controller is crucial as a deficiency in communication could have negative impact on system security, reliability, and safety. Depending on the size of the wind generation, SCADA systems are employed for remote monitoring, data acquisition, and open and closed loop control for the wind tribunes. For instance, in a real implementation in Canada, SCADA systems enable users to tune system parameters like wind energy converter and voltage control system to achieve desired generation output [163].

6.2.2. Communication systems for photovoltaic systems

Similar to the previous case, communication system gets the information from power inverters deliver this information for connection status, real and reactive power generation, and voltage. Advanced systems can provide more information such as solar irradiance, ambient temperatures, etc. The most common protocol between the inverters and the data logger is RS-485. Moreover, the performance of the solar generation can easily be degraded by shading, dust, or tree limbs. Hence, for fault diagnosis at the individual panel level, Zigbee communications is widely used [163].

6.3. Communication standards

A fully functional smart grid needs a large number of protection, control and monitoring devices located across a large geographic area to perform various distributed energy management (DEM) operations such as wide-area situational awareness, distribution automation and demand response. Hence, the corresponding communications system needs to operate in different propagation and deployment scenarios at different parts of the grid. Moreover, allocation of network resources (i.e. signaling and traffic) and guarantee of QoS (quality-of-service) among multiple DEM applications pose additional challenges. In such a paradigm, multi-domain resource allocation and QoS control functionalities such as hierarchical data aggregation and group resource allocation can significantly enhance the performance of the overall network and optimize its available resources.

With a view to meet the aforementioned challenges, a multi-tier heterogeneous network (Hetnet) architecture has been developed which is comprised of a primary network based on a long-range wireless technology such as UMTS/LTE/WiMAX and one or more secondary network based on short/medium range wireless technologies such as IEEE 802.15.4 based ZigBee and IEEE 802.11 based WLAN (Wireless Local Area Network) networks. A conceptual model of this network architecture is shown in Fig. 18.

A resource management entity is the key enabler of this architecture that adaptively and opportunistically varies radio resources, i.e. signaling and traffic channels among the transmission links to meet the QoS requirements of each active connection. There are several advantages of this architecture, such as:

(1) The architecture provides physical separation between the home area network (HAN) and the wide area network (WAN) of the smart grid communications system which improves security, resolves ownership issues, and encourages development of new independent HAN and WAN applications.
(2) The access points/coordinators of the secondary network can act as Hetnet relays for the primary network which can extend the range, improve link quality, and eliminate dead spots of the overall wireless network.
(3) The end-devices may considerably save the transmit power due to improved SNR (signal-to-noise ratio) values. The improved link margin will also allow the primary network links to operate on a higher modulation and coding scheme (MCS) which can significantly increase the overall data rate of the network.
(4) The hybrid network can use spectrums from both licensed and licensed-exempt bands which could increase the spectrum efficiency of the system without raising the interference margin.
(5) The end devices can use relatively less expensive WLAN, ZigBee chips which may reduce the overall cost of the network deployment
(6) The secondary networks can aggregate the traffic from multiple nodes into a single data burst which will reduce the amount of network access in the primary network which in turn will improve its data transmission efficiency by reducing the amount of signaling and protocol overheads.

6.4. Sensor technologies

The proliferation of sensor and monitoring technologies are key

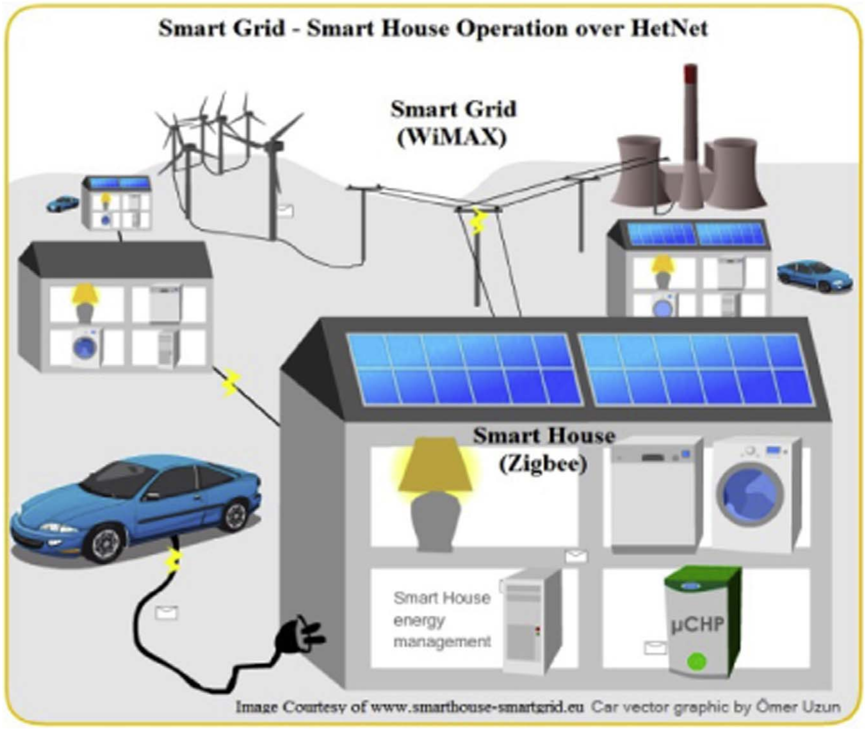

Fig. 18. Smart home design with BTM equipment.

enabling technologies for the behind the meter energy management systems. In its current state, the demand response programs depend on the manual load shifting. Hence they have limited applicability. Therefore, there is a tremendous potential for sensor networks applications. Furthermore, traditional power system monitoring and fault diagnostics systems employ wired communications, which are very costly and hard to maintain. To that end, wireless sensor networks (WSN) have significant benefits over their wired counterparts. The work in [164] explores the applications of presents the statistical characterization of the WSN for smart grid measurement and diagnostics applications. On the other hand studies in [165] and [166] employ WSNs for residential home energy management systems.

6.5. Smart plugs

Smart Plugs embed the sensing, communication, and control technologies to provide real-time electricity usage information to users or an automated end-user. There are three basic functionalities of smart plugs: (i) Perform current and basic power quality measurements; (ii) Communication the measured data with the user via Zigbee, WiFi, HomePlug, etc.; (iii) Control the power usage of the appliances by turning On/Off. To this end, there has been an enormous interest in developing new solutions by the electronics manufacturers [167–170].

6.6. Cyber-security

The operations of the BTM system rely heavily on the communication technologies. The integration of information systems transforms the power grid into a massive cyber-physical system. Because the access to electric power is vital to human life, if not secured, the malicious adversary can harm the physical infrastructure. Potential cybersecurity threats include RF jamming, wireless scrambling, protocol failures, eavesdropping, and message modification and injection [161]. Another concern is related to protecting the personal consumption information of users. If there is an eavesdropping attack, customer's lifestyle, when the customer is at home or not, which appliances is being used, etc. can be used by criminals. [171].

6.7. Behind-the-meter (BTM) EV-smarthome integration with IEC 61850 standard

Establishing a common language that can be understood by every equipment in BTM systems holds key importance for a successful implementation. Considering that numerous power equipment companies exist, and each uses its modeling for communication and control, it is inevitable that a network of electrical devices (such as SmartHouse or smart grid) turns into a pile of nodes that cannot communicate. Such interfacing problem as well as established standard language in BTMs is illustrated in Fig. 19. To tackle this, IEC 61850, a substation communication standard has been published [172]. Soon after its publication, IEC 61850 received much attention in power engineering circles as it addressed a vital aspect of communication lines in power systems. In an effort to encourage its utilization in microgrids, which have more DG deployments, the International Electrotechnical Commission formed Workgroup (WG17) to publish an extension of IEC 61850-7-4: Compatible logical node (LN) classes and data classes. This extension aimed at developing LNs and data classes to standardize the modeling of DER systems. The overall generic system is given in Fig. 20 is used as a template for modeling the DER systems such as Diesel Generators, Solar panels (PV), Fuel Cells, and Combined Heat and Power. In addition to function of switching DERs on and off, DER systems also involve:

(1) Management of the interconnection between the DER units and the power systems they connect to, including local power systems, switches and circuit breakers, and protection.
(2) Monitoring and controlling the DER units as producers of electrical energy.
(3) Monitoring and controlling the individual generators, excitation systems, and inverters/converters.
(4) Monitoring and controlling the energy conversion systems, such as reciprocating engines (e.g., diesel engines), fuel cells, photovoltaic systems, and combined heat and power systems.
(5) Monitoring and controlling the auxiliary systems, such as interval meters, fuel systems, and batteries.

Fig. 19. Challenge of unique languages vs. standard language in BTM systems.

(6) Monitoring the physical characteristics of equipment, such as temperature, pressure, heat, vibration, flow, emissions, and meteorological information.

The system assumes a holistic sense in which the DER systems are modeled starting from their internal parameters (e.g., fuel type for diesel generators, battery test results for solar panels or hydrogen levels for fuel cells) to their grid connection types and parameters and even microgrid operator commands and control units. Having detailed characteristic variables and measurement values entrenched inside; this modeling system serves for a rigorous communication system. To give a better insight about DER systems modeling, the new LN classes and data classes shall be explained in four groups; DER unit controller, internal parameters, grid connection and network operator units [173,174]. This extension to IEC 61850 standard enables power system engineers to model entire BTMs that are as large as full smart grids, with IEC 61850 and IEC 61850-7-420 standards [175].

The large acceptance of EVs will have impacts on electrical networks. It is expected that V2G shall be one of the key technologies in smart grid strategies [75,77,176,177]. By making use of V2G technology, EVs not only draw power from the network but also act as distributed storage devices and support it during peak-load times. Through demand side management and demand response, the charge and discharge times of EVs can be scheduled by the load profile [76,178]. In this manner, EV owners can sell the stored energy in their vehicles' batteries during peak times and recharge them once the peak hour expires and the price reduces. It is possible to pool several EVs together and provide larger support to the networks where owners can obtain incentive costs. In order to achieve all of these advantages there shall be communication and synchronization between the components

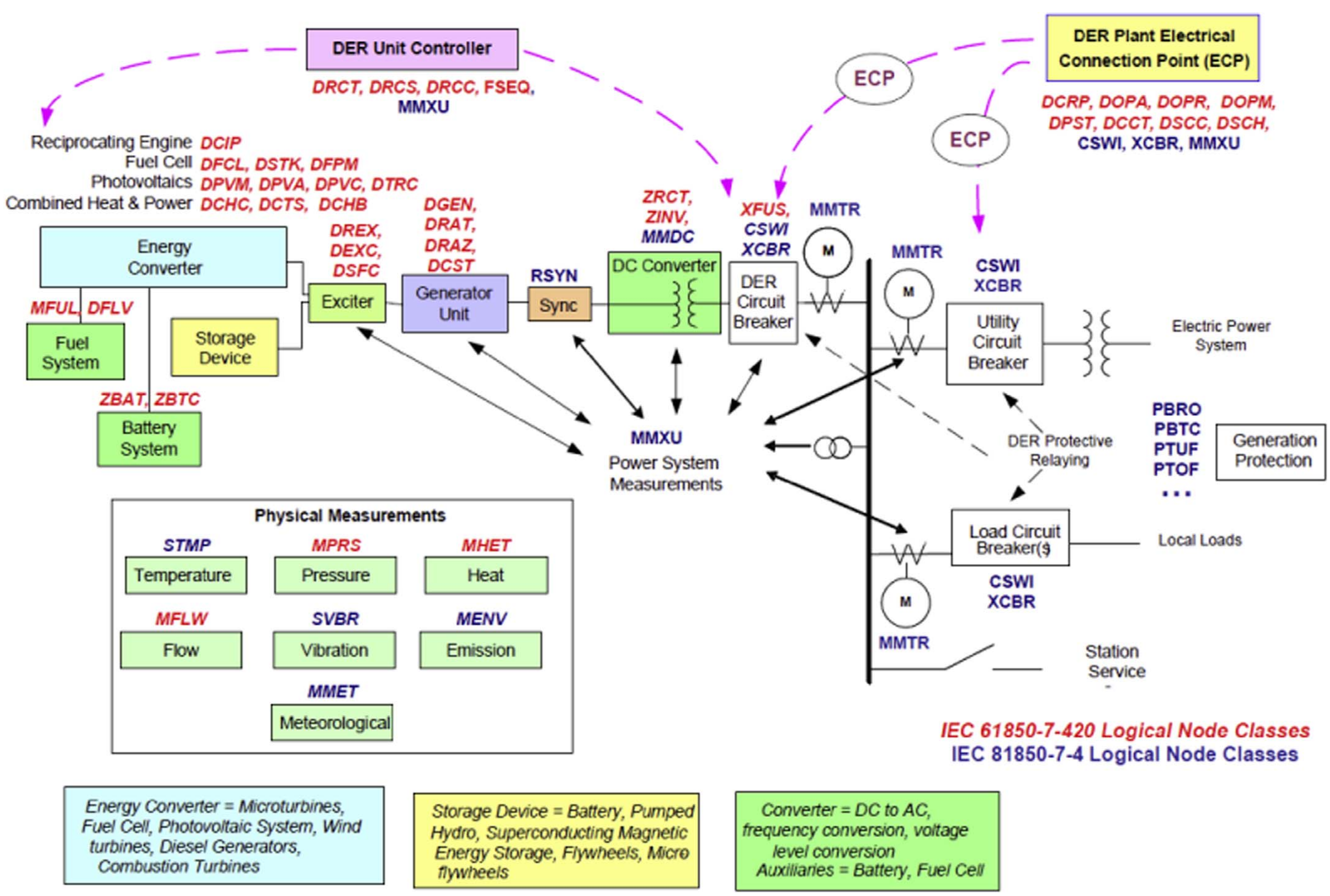

Fig. 20. Generic DER system in IEC 61850-7-420, modeling is done beyond MMTR which represents the meter [?].

of smart grids. Similar to other electrical network components, EVs should also be modeled in communication systems. This is important to receive crucial information such as the battery size of the vehicle, amount of the stored energy, time period when V2G is allowed by the owner and the time when EV is required to be fully charged. If these data are provided, network operators can exercise more precise planning and smart grids can be used more effectively and efficiently.

IEC 61850-7-420 standard focuses on DER modeling. However, it does not cover EVs and the functions related to EVs. It is possible to model EVs as distributed storage systems with a smart charging and discharging control. Although EVs could be mostly considered as load elements on the system consuming electrical power, they could also act as a resource at times of peak demand for example when most EVs would be parked in garages and hence could be used to support peak demand load. Thus, it makes sense that a Logical Node (LN) model gets included in the IEC 61850-7-420 to cover EVs.

A Logical Node (LN) is a sub-function located in a physical node, which exchanges data with other separate logical entities. LNs are virtual representations of real devices. In IEC 61850-7-420, the standardized name of the LN implementing the task of a DER controller is DRCT. The DER controller (DRCT) LN defines the control characteristics and capabilities of one DER unit or aggregations of one type of DER device with a single controller.

In IEC 61850-7-420, the battery and its charger are modeled with ZBAT and ZBCT classes. The grid connection of the EV is realized through a dc switch, modeled with CSWI and XSWI, and an inverter, modeled with ZCRT and ZINV. Fig. 21 shows the block diagram representation of EV model in data communication world. ZBAT, ZBTC, CSWI, XSWI, ZRCT, and ZINV all represent application-view data models that represent some aspect of the charging/discharging of the EV. These models could be aggregated together to represent the overall function of charging/discharging of an EV. As per the IEC 61850 syntax, such an aggregation is called forming a Logical Device (LD) model. LD models represent information about the resources of the host itself including real equipment connected and the common communication aspects applicable to a number of LNs. What is missing in Fig. 21, which represents the device-view model of an EV charging/discharging function, is a sub-function (LN) that controls the charging and discharging process and the interaction of individual elements. Hence, a new LN class called Electric Vehicle Control (EVCT) has been developed as shown in Table 3 to reflect the sub-function required for monitoring the critical functions and states of the V2G process [179]. The EVCT LN node will hold the answers to the following questions:

(1) When to start the vehicle-to-grid (discharge) process?
(2) At what time during the day or night should the battery be fully charged?
(3) When to charge the car?
(4) Is demand side response in operation? Is Economy charging out of peak-hours or immediate charging at the time of connection?
(5) How much power has been supplied to the grid? How much imported?

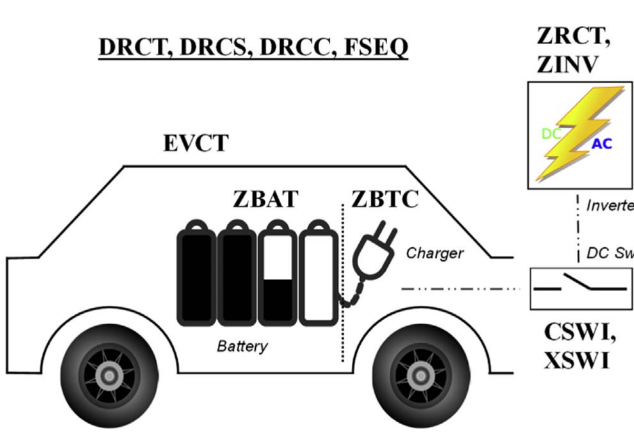

Fig. 21. Modeling EVs with IEC 61850-7-420.

Table 6
EVCT class developed in [179].

EVCT class				
Data name	**CDC**	**Explanation**	**T**	**M/O/C**
LN name		Shall be inherited from logical-node class (see IEC 61850-7-2)		
Data				
System logical node data				
		LN shall inherit all mandotary data from common logical node class		M
		Data from LLN0 may optionally be used		O
Settings				
V2GStart	ASG	V2G-Allowed Period Start Time		O
V2GEnd	ASG	V2G-Allowed Period End Time		O
ChrgReady	ASG	Time when EV should be fully charged		O
Alim	ASG	Input current limit		O
Vlim	ASG	Input voltage limit		O
ChrgMode	ING	Charging Mode (see IEC 61851-1)		M
Status information				
ConnCount	INS	Count of Grid Connection		M
V2GStatus	SPS	True: V2G Participation is ON False: V2G Participation is OFF		M
EconStatus	SPS	True: Economic Charging is selected False: Immediate Charging is Selected		M
Charging-Signal	SPS	True: Charging Indicator is ON False: Charging Indicator is OFF		O
BattFullAudibleSignal	SPS	True: Battery Full Audible Signal is ON False: Battery Full Audible Signal is OFF		O
Controls				
V2GEnable	DPC	Switch On/Off V2G participation, On=True, Off=False		M
EconCharge	DPC	Toggle between Economic and Immediate Charging, Economy=True, Immediate=False		M
Measured values				
Supplied-Power	MV	The amount of power supplied to Grid through V2G scheme		O
Received-Power	MV	Power received for charging the batteries		O

In other words, the EVCT class defines the data about the V2G process under four categories, i.e., Settings, Status In-formation, Controls, and Measured Values. The class model is shown in Table 6 is self-explanatory. However, specific data items could be further explained below.

The settings section includes five items. Through these, in relation to load profiles and peak times, the owner or the network operator can assign V2G start and end times. “ChrgReady” indicates the time when the owner desires EV to be fully charged and ready to move. The “Alim” and “Vlim” denote the input and voltage current limits for the charging process. These current and voltage values shall be in compliance with the standard IEC 61851-22: AC electric vehicle charging station [180]. This standard stipulates upper and lower limits for voltage, current, and frequency for different countries. This way it is ensured that the proposed EVCT class can be used worldwide. ChrgMode parameter holds the value for the selected charging mode among the modes defined by IEC 61851-1: Electric Vehicle Conductive Charging System, General Requirements [181]. This parameter is vital for providing a standard LN for EVs since different countries have different grid parameters and grid codes. For instance, Mode 1 Charging can be used with standardized socket-outlets not exceeding 16 A and not exceeding 250 V AC single-phase or 480 V AC three-phase [181]. An additional earth conductor is also required for these outlets. However, mode one charging is prohibited in the United States by national codes while Japan and Sweden allow it for domestic use. In this fashion, IEC 61851 is utilized to overcome the varying nature of grids around the world. It is a great advantage that both of the standards used in EVCT LN, i.e., IEC 61851 and IEC 61850, are prepared by the IEC. This means they are compatible and complementary with each other. First, three items in status information section are mandatory. ConnCount keeps the grid connection count for lifetime estimation and maintenance purposes. “V2GStatus” indicates whether the EV under consideration participates in V2G while “EconStatus” indicates whether the owner opts for economic charging during non-peak times or immediate charging regardless of the cost. Last two variables show the status of visible and audible signals. ChargingSignal relates to the visual indicator which shows that charging is in progress while BattFullAudibleSignal represents.

There are two control inputs to control V2G participation and economic charging, “V2GEnable” and “EconCharge”. These can be toggled either locally by the owner for demand response or by the central network control for demand side management. The optional measurements are aimed at keeping record of energy transfer between the grid and the EV. However, measurement can also be performed through smart meters and in that case separate modeling would be required.

The overall modeling of EV with IEC 61850-7-420 for SmartHome integration in BTM is shown in Fig. 22. EVCT class is the interface between battery system and grid connection. ZBAT and ZBTC classes can be fully adopted as it has very comprehensive battery and charging information [173]. Similar to fuel cells and solar panels, EVs are connected to grid over a dc switch and an inverter. These models can be used for an individual EV as well as aggregated V2G pools which consist of several EVs. The generic nature of EVCT class makes the proposed model very versatile. Various EVs produced by different manufacturers can be conveniently modeled and used separately or in a pool. The integration between car manufacturers, SmartHome controllers and the network operators becomes trivial thanks to the developed method of presenting EV parameters in a standard fashion. In short, using a standard communication for smart devices in BTM is of great importance for smooth operation and easy integration. There are several standards which can be used for different purposes. IEC 61850 is a promising standard that is always developing and expanding. As shown in this section, holistic BTM systems, i.e., SmartHomes with EVs, can be modeled with this standard. Further investigation is required to create a universally accepted standard language for BTM communication and control.

7. Case study: smart farm-smart grid integration with BTM

Precision Agriculture (PA) is a farm management approach that uses information technology, satellite positioning data, remote sensing and proximal data gathering to optimize returns on inputs while potentially reducing environmental impacts [182]. It uses ubiquitous sensing technologies, smart Decision Support Systems (DSS) and location aware actuators to implement selective field interventions at specified locations using information obtained from the field sensors and analyzed using DSS. Being deployed with smart systems, Smart Farms offer attractive opportunities for Smart Grid Integration [183]. Simply put, Smart Farm-Smart Grid integration can be used to maximize Smart Grid availability with the support from Smart Farm. On the other hand, Smart Farm owners may enjoy generous incentives for their grid-support. The biggest benefit from such integration is the ability to report possible events in Smart Farm to the Smart Grid operator. For instance, during harvest time, when it is determined that the crops are ready for harvest, Smart Grid can be notified of a certain amount of biomass availability after a certain amount of time, i.e. harvesting and collection time.

7.1. Sensors

Sensors collect information about field conditions enabling a mapping of field conditions and differentiation of variability. Information is collected about crop factors such as disease infestation, nutrient, water stress and soil factors such as fertility moisture, electrical conductivity and environmental conditions such as air temperature [184]. Information is collected using spectroscopic means and directly through physical and chemical measurements. Smart Farm employs different categories of sensors; the first and perhaps most important category are in-field sensors. These have been enabled by integration with and even reliable communication technologies such as ZigBee, Wi-Fi, and GSM. These sensors combine the sensor suite with wireless communication device into a single device which can take measurements and relay them at any time. These are deployed optimally in the field to ensure an optimal coverage of the field enabling efficient and accurate mapping [185] Aerial borne sensors are also used in agriculture, in particular unmanned aerial vehicles [184] which are replacing the use of satellites due to the latter's temporal limitations and reliance on open skies for accurate sensing. Finally, sensors can be mounted on location aware mobile platforms.

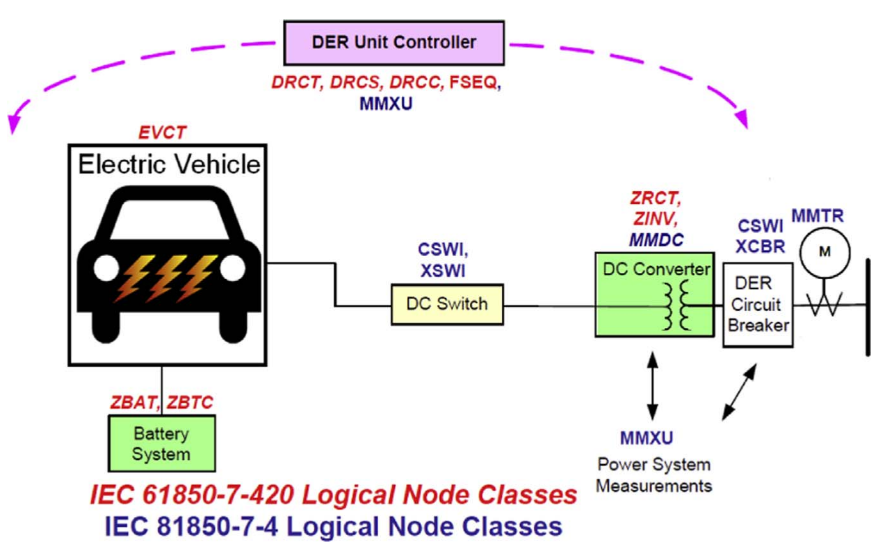

Fig. 22. Developed EVCT class used in SmartHome integration for BTM.

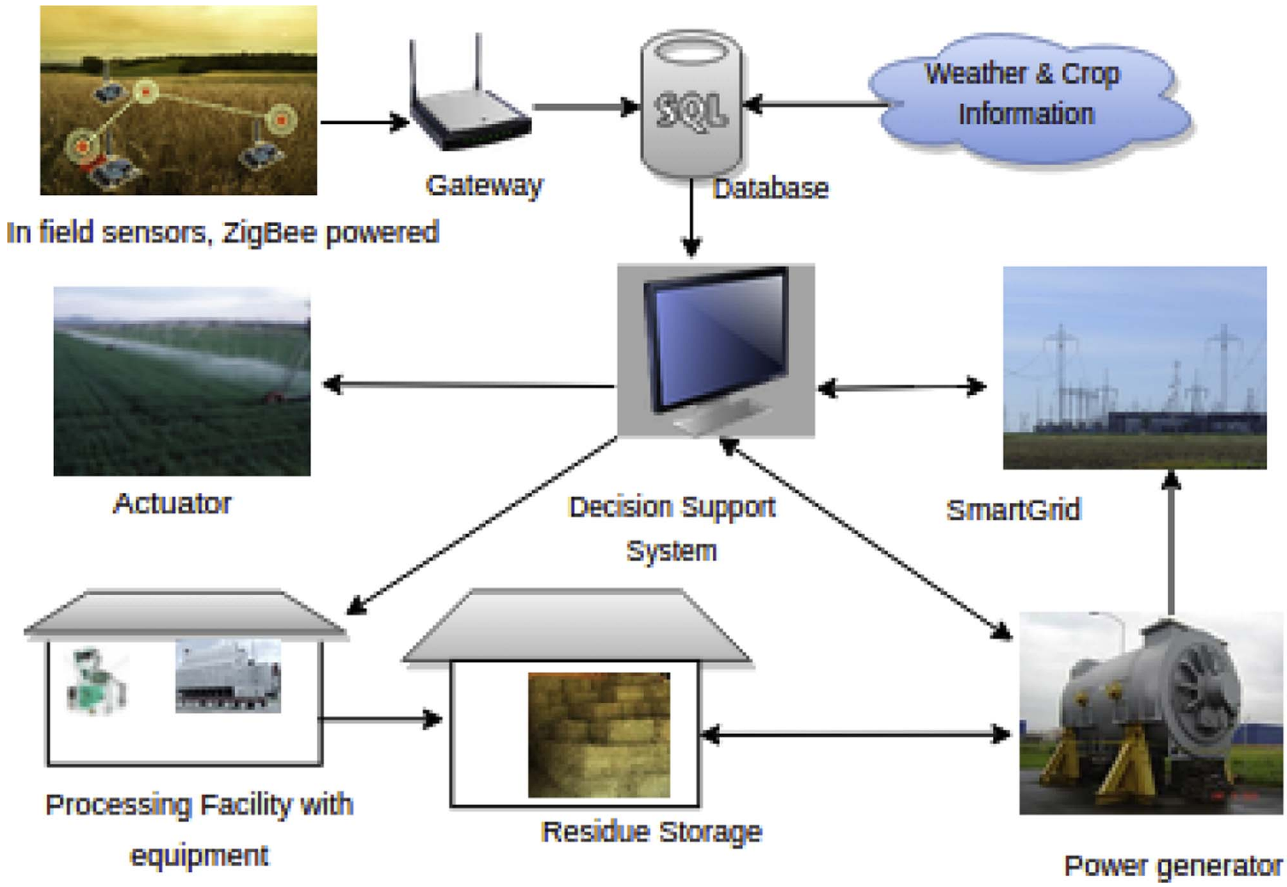

Fig. 23. Deployment of a smart farm integrated with smart grid.

7.2. Decision support systems (DSSs)

Generally, geographical information system (GIS) database types such as POST-GIS are used in precision agriculture [186]. GIS applications provide methods for analysis and interpolation of data such as if Krigging analysis to convert point data into spatial data. The information obtained from sensors is converted into a format consistent with the specific parameters of interest using given benchmarks from knowledge databases. An example is the NDVI index calculation from the spectral reflectance of points in the field. These analyzed data sets are then interpolated (where necessary) to create a continuous spatial map of the parameters of interest. The decision support interface provides platforms for exporting the data to variable rate actuators which enable execution of implementations.

7.3. Actuators

Implementation of actuators requires, in general, location knowledge which is provided by embedded GPS devices. These devices need to be augmented to increase their accuracy to the centimeter level. The actuators also have software to allow loading of maps and hardware to implement variable interventions basing on the maps. Examples include; auto-steer agricultural machinery powered using real-time kinematics (RTK), light bar guidance systems where drivers are guided using the horizontal display of lights. Differential GPS systems are also used to implement actuators where a reference point with a known GPS coordinate within the farm is used to increase the accuracy of the GPS readings. Before an intervention, the relevant encoded treatments are loaded onto the vehicles (variable rate applicators). The variable rate applicators as they move through the field, read the current GPS location (corrected) and using this information and information loaded onto their drives to apply differential treatments to the given location.

The developed BTM model shown in Fig. 23 [183] considers an integration of a Smart Farm and Smart Grid. The Smart Farm has in-field sensors with a gateway node. The Sensors connect to a database through a gateway using ZigBee standard. The database has connections to a local weather station for weather prediction and a knowledge database. The local weather station provides local weather forecasting. A DSS available through a computer terminal helps in analyzing and presenting information to the user for decision making. In order to support the integration, the DSS will be modified to be able to perform the energy computations relating to load estimation and energy generation estimation as specified above. The model also includes a CHP for power generation. This is supported by a storage facility for agricultural residue sufficient to provide material for up to one season. Actuators help implement corrective measures. There is also a processing facility for crop production.

Fig. 24 shows a comparison of the conventional and developed DSS models for Smart Farms [183]. As shown, the proposed model incorporates connections to the Smart Grid and utility providers. The model operates as follows; a Smart Farm having sensor devices captures relevant information such as reflectance metrics periodically and sends it through the gateway to the data center. Using relevant

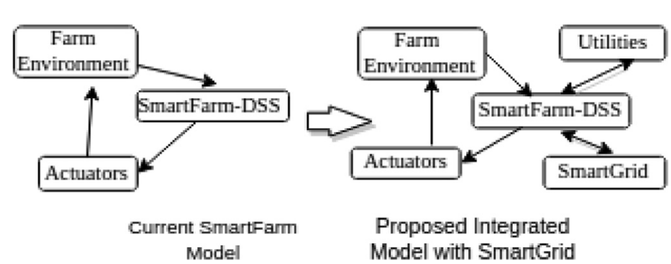

Fig. 24. Conventional and developed models of smart farm DSS.

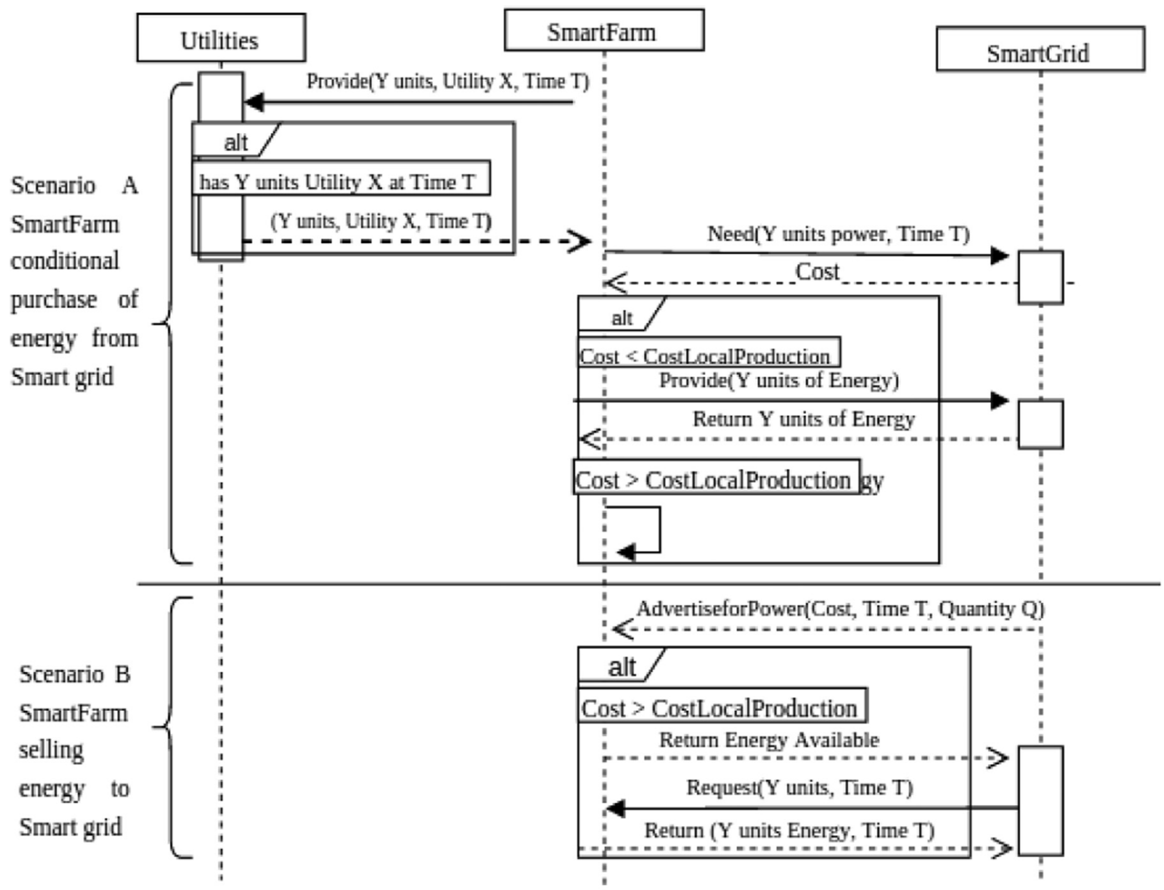

Fig. 25. Communication between SmartFarm. Smart grid and utilities.

algorithms which are specific to different scenarios and information from cloud about the specific crops, it is decided if the data presented necessitates intervention. In the event that there is a need for intervention, information from the weather station is used to make predictions on the suitability of weather conditions for intervention. The weather data could nullify the need for intervention in some cases such as in the case of irrigation. In the case of application of fertilizers and or pesticides, the occurrence of rain after application would result in leaching. This is not only wasteful but also harmful for the environment.

If the conditions are right and an intervention will be made, Smart Farm communicates with utility agents who can help reduce storage costs for farms. Smart Farm requests for an amount of utility relevant to the intervention. After getting availability assurance from the utility agent, Smart Farm talks to the Smart Grid requesting the cost and availability of the required quantity of power. This process is illustrated in the sequence diagram given Fig. 25 [183]. Smart Grid relays the energy cost. Smart Farm can then makes a decision to either buy power or to generate from its reserves for the intervention by comparing this power cost with the cost of production from its residue storage. Consideration is also made for the smart grid to obtain energy from Smartfarm and for Smartfarm to sell energy to the Smart grid, if possible.

The Smart Grid advertises for a specific amount of energy at a specific cost at a specific time at which it will require energy from Smart Farm based on its estimated load. Smart Farm compares the cost being offered with its cost of producing power. If the electricity being offered is greater than its cost, it then determines the amount of residue it can use for generating power considering availability of residue and the time it will take before residue can be obtained again. This is calculated as shown in Eq. (2) below

$$RU = TR - MBR \tag{2}$$

where RU is the residue available for combustion, TR is the total volume of residue available and MBR is the Minimum buffer residue that can be allowed in the system. MBR is a function of the time until next residue can be obtained, e.g., from the harvest and the average consumption of residue per unit time being considered, as in (3).

$$MBR = \text{Daily Usage} \times \text{Time until next harvest} \tag{3}$$

The energy available can then be calculated as

$$EA = RAxE \tag{4}$$

where EA is the energy available, RA is the residue available and E is the energy per unit of residue. The Smart Farm then communicates to the Smart Grid on the amount of energy it can provide using its reserves enabling a contract to be made.

With the help of BTM Smart Farm operations, Smart Farms act as a single smart entity through its interface with Smart Grid. During times of energy demand, Smart Farm acts as a smart load which notifies Smart Grid its demand and approximate time. At times of excess energy, Smart Farm acts as a smart generator which supports Smart Grid by going online, whenever such support is required.

Due to isolated, or rural, nature of Smart Farms, this integration can be used as a backbone for rural electrification endeavors. For instance, if the excess energy permits it, some residential houses around Smart Farm can be included in BTM system as loads, and much-needed electrification can be achieved. As the time progresses, such Smart Farm-Smart Grid integration may help span the entire country and increase rural electrification rate.

8. Conclusions

BTM systems are gaining more acceptance as they are addressing challenges posed by the changing paradigms of power systems such as renewable energy penetration, environmental concerns as well as the introduction of new technologies and business models. As discussed in the manuscript, the impacts of BTMs span different domains, namely technology, economy, and society.

On the technology front, it is a well-acknowledged fact that power systems are becoming more heterogeneous and unorthodox with different mixes of generation and consumption technologies. BTM systems have the ability to facilitate inclusion and integration of them with smart and enhanced control. Smart algorithms implemented in a BTM system can reduce the impact of intermittency posed by renewable energy based distributed generators. Local consumption may be matched with the renewable energy available and this supply-demand arrangement achieved before the meter helps mitigate its effect on the large-scale interconnected grid.

As far as the economy is concerned, novel developments in the power system field require more granular control of the power flow at the distribution level and fine-grained accounting of the generation and consumption. In contrast to traditional power system operation that is based on bulk-energy trading between large companies, microgrids require monitoring generation and consumption of a single household and calculation of balances based on a complicated mix of tariffs. BTM systems offer the necessary communication, standardization and automation required to achieve all of these tasks.

Finally, new-age grids require supply of power in a more consumer-based approach. It is required to study the consumer behavior, its underlying reasons and the resultant load-profiles. Detection of consumption patterns may ease grid-planning and, if possible, necessary interventions may be utilized to change them. BTM systems can collect and report data, implement different charging schemes for demand-side response purposes and analyze the effectiveness of the scheme which is currently implemented.

Furthermore, BTM systems can be utilized for integration of smart grids with other components such as SmartFarms. Such an integration will maximize the energy efficiency in farms, reduce their energy bills and increase their crop yield while the grid operators will benefit from increased grid-support and reliability. This is not limited to farms and different integration models including shopping centers, commercial buildings and schools can be investigated. In all of these cases, BTM systems are required to have a distributed control on the consumer side for coordination and control.

In short, power systems are experiencing unprecedented changes. The bulky, centrally-controlled, interconnected systems are being replaced with microgrids that include distributed generators, often renewable energy based. These microgrids include ubiquitous monitoring and more distributed control. In order to address these new requirements, BTM systems are developed and deployed. They offer numerous advantages on different fronts such as technology and economy, and facilitate the transition to the grid of the future.

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