Optimizing Shiftable Appliance Schedules across Residential Neighbourhoods for Lower Energy Costs and Fair Billing

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Abstract. This early stage interdisciplinary research contributes to smart grid advancements by integrating information and communications technology and electric power systems. It aims at tackling the drawbacks of current demand-side energy management schemes by developing an agent-based energy management system that coordinates and optimizes neighbourhood-level aggregate power load. In this paper, we report on the implementation of an energy consumption scheduler for rescheduling "shiftable" household appliances at the household-level; the scheduler takes into account the consumer's time preferences, the total hourly power consumption across neighbouring households, and a fair electricity billing mechanism. This scheduler is to be deployed in an autonomous and distributed residential energy management system to avoid load synchronization, reduce utility energy costs, and improve the load factor of the aggregate power load.

1 Introduction

Electric utilities tend to meet growing consumer energy demand by expanding their generation capacities, especially capital-intensive peak power plants (also known as "peakers"), which are much more costly to operate than base load power plants. As this strategy results in highly inefficient consumption behaviours and under-utilized power systems, demand-side energy management schemes aiming to optimally match power supply and demand have emerged.

Currently deployed demand-side energy management schemes are based on the interactions between the electric utility and a single household [18], as in Fig.1(a). As this approach lacks coordination among neighbouring households sharing the same low-voltage distribution network, it may cause load synchronization problems where new peaks arise in off-peak hours [15]. Thus, it is essential to develop flexible and scalable energy management systems that coordinate energy usage between neighbouring households, as in Fig.1(b).

2 Background

The smart grid, or the modernized electric grid, is a complex system comprising a number of heterogeneous control, communication, computation, and electric

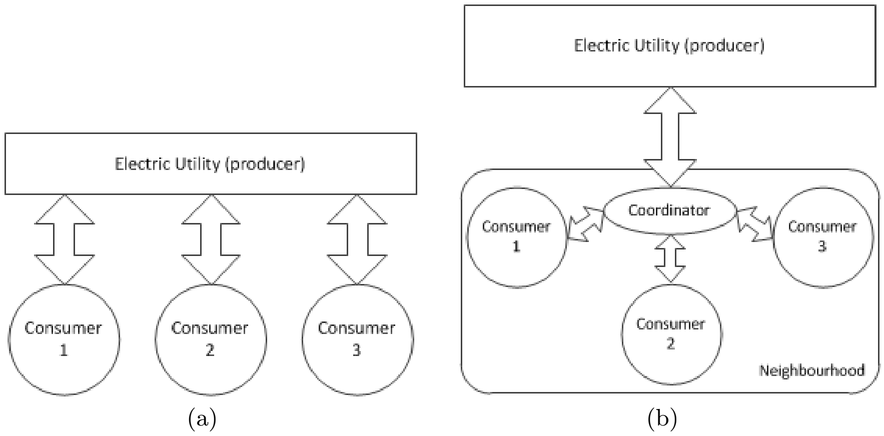

Fig. 1. The interactions between the utility and the consumers in demand-side energy management schemes are either: (a) individual interactions, or (b) neighbourhood-level interactions

power components. It also integrates humans in decision making. To verify the states of smart grid components in a simultaneous manner and take human intervention into account, it is necessary to adopt autonomous distributed system architectures whose functionality can be modelled and verified using agent-based modelling and simulation.

Multi-agent systems (MAS) provide the properties required to coordinate the interactions between smart grid components and solve complex problems in a flexible approach. In the context of a smart grid, agents represent producers, consumers, and aggregators at different scales of operation, e.g. wholesale and retail energy traders [7]. MAS have been deployed in a number of smart grid applications, with a more recent focus on micro-grid control [6, 17] and energy management [10, 12] especially due to the emerging trend of integrating distributed energy resources (DER), storage capacities, and plug-in hybrid electric vehicles (PHEV) into consumer premises.

In agent-based energy management systems, agents may aim at achieving a single objective or a multitude of objectives; typical objectives include: balancing energy supply and demand [4]; reducing peak power demand [13, 16]; reducing utility energy costs [8, 16] and consumer bills [16]; improving grid efficiency [4]; and increasing the share of renewable energy sources [1, 12] which consequently reduces the carbon footprint of the power grid. Agent objectives can be achieved using evolutionary algorithms [8] or a number of optimization techniques such as integer, quadratic [5, 13], stochastic [4] and dynamic programming [5]. As for the interactions among agents, game theory provides a conceptual and a formal analytical framework that enables the study of those complex interactions [19].

3 Research Objectives

This research aims at optimizing the energy demand of a group of neighbouring households, to reduce utility costs by using energy at off-peak periods, avoid load synchronization that may occur due to rescheduling appliance usage, and improve the load factor (i.e. the ratio between average and peak power) of the aggregate load. A number of energy consumption schedulers have been proposed in the literature [14, 16, 21]; however, those schedulers do not leverage an accurately quantified and fair billing mechanism that charges consumers based on the shape of their power load profiles and their actual contribution in reducing energy generation costs for electric utilities [3]. In this paper, we implement and evaluate an energy consumption scheduler that optimizes the operation times of three wet home appliances and a PHEV at the household-level based on the total hourly power consumption across neighbouring households, consumer time preferences, and a fair electricity billing mechanism.

4 Methodology

We use the findings of Baharlouei et al. [3] to resolve a gap in the findings of Mohsenian-Rad et al. [16]. Game-theoretic analysis is used by Mohsenian-Rad et al. [16] to propose an incentive-based *energy consumption game* that schedules "shiftable" home appliances (e.g. washing machine, tumble dryer, dish washer, and PHEV) for residential consumers (players) according to their daily time preferences (strategies); at the Nash equilibrium of the proposed non-cooperative game, it is shown that the energy costs of the system are minimized. However, this game charges consumers based on their total daily electric energy consumption rather than their hourly energy consumption. In other words, two consumers having the same total daily energy consumption are charged equally even if their hourly load profiles are different. This unfair billing mechanism may thus discourage consumer participation as it does not take consumer rescheduling flexibility into consideration. With this in mind, we propose leveraging the fair billing mechanism recently proposed by Baharlouei et al. [3] to encourage consumer participation in the energy consumption game.

5 Energy Consumption Scheduler

5.1 Formulation

Assuming a multi-agent system for managing electric energy consumption at the neighbourhood-level, where agents represent consumers, each agent locally and optimally schedules his "shiftable" home appliances to minimize his electricity bill taking into account the following inputs: appliance load profiles, consumer time preferences, grid limitations (if any), aggregate scheduled hourly energy consumption of all the other agents in the neighbourhood, and the deployed electricity billing scheme. If the energy cost function is non-linear, knowing the aggregate scheduled load is required for optimization.

After this optimization, each agent sends out his updated appliance schedule to an aggregator agent, which then forwards the aggregated load to the other agents to optimize their schedules accordingly. By starting with random initial schedules, convergence of the distributed algorithm is guaranteed if household-level energy schedule updates are asynchronous [16]. The electric utility may coordinate such updates according to any turn-taking scenario.

We assume electricity distributed to the neighbourhood is generated by a thermal power generator having a quadratic hourly cost function [23] given by (1); as this equation is convex, quadratic, and has linear constraints, it can be solved using mixed integer quadratic programming.

$$C_h\left(L_h\right) = a_h L_h^2 + b_h L_h + c_h, \tag{1}$$

where $a_h > 0$, and b_h, $c_h \geq 0$ at each hour $h \in H = [1, ..., 24]$. In (2), L_h and x_m^h denote the total hourly load of N consumers and consumer m, respectively [16].

$$L_h = \sum_{m=1}^{N} x_m^h, \tag{2}$$

To encourage participation in energy management programmes, it is essential to reward consumers with fair incentives. By rescheduling appliances to off-peak hours where electricity tariffs are cheaper, we save on utility energy costs and consequently impose monetary incentives for consumers in the form of savings on electricity bills. The optimization problem therefore targets the appliance schedule x_n^h that results in the minimum bill B_n for consumer (agent) n. The billing equation proposed by Baharlouei et al. [3], which fairly maps a consumer's bill to energy costs (1), is given by (3).

$$B_n = \sum_{h=1}^{H} \frac{x_n^h}{\sum_{m=1}^{N} x_m^h} C_h\left(\sum_{m=1}^{N} x_m^h\right), \tag{3}$$

5.2 Set-up

To model the optimization problem such that each agent n individually and iteratively minimizes (3), we use YALMIP — an open-source modelling language that integrates with MATLAB. We consider a system of three households (agents) and investigate the behaviour of one of those schedulers with respect to fair billing, lower energy costs, and improved load factor. To model consumer flexibility in scheduling, we consider two scenarios for the same household where the consumer's acceptance of rescheduling flexibility differ. We investigate the two scenarios for four days in December, March, June and September.

To test our energy consumption scheduler, we choose to schedule a PHEV and three wet appliances: a clothes washer, a tumble dryer, and a dish washer. Wet appliance power load profiles are based on survey EUP14-07b [22], which was conducted with around 2500 consumers from 10 European countries. For the PHEV load, we use the power load profile of a mid-size sedan at 240V–30A [9].

We choose a budget-balanced billing system and calibrate the coefficients of the hourly energy cost function (1) against a three-level time-of-use pricing scheme used by London Hydro [11], where the kilowatt-hour is charged at 12.4, 10.4, and 6.7 cents for on-, mid-, and off-peak hours, respectively. Energy consumption of neighbouring households and non-shiftable loads of the household investigated are taken from a publicly available household electric power consumption data set [2], for the period from December 2006 to September 2007.

5.3 Scenario 1

In this scenario, we assume the consumer is not flexible about appliance scheduling and use common startup times: clothes washing starts at 7 a.m., drying starts two hours directly after washing starts, dish washing starts at 6 p.m. [22], and PHEV recharging starts at 6 p.m. [20].

5.4 Scenario 2

The consumer is assumed to be flexible about appliance scheduling in Scenario 2; clothes washing starts any time between 6 a.m. and 9 a.m., drying any time after washing but before 11 p.m., washing dishes any time after 7 p.m, but before 11 p.m., and PHEV recharging any time after 1 a.m. but before 5 a.m.

6 Results

6.1 Fair Billing

Results indicate that the consumer's electricity bill for operating household "shiftable" appliances in Scenario 2 is lower by 70%, 57%, 32%, and 65% compared to that in Scenario 1 for the days chosen in December, March, June, and September, respectively. This clearly indicates that flexibility is awarded fairly through the deployed billing mechanism. Figures 2 and 3 depict the appliance schedules resulting in the minimum bill for the household under investigation and the aggregate non-shiftable load of neighbouring households, for Scenario 1 and 2 in December, respectively.

6.2 Lower Energy Costs

As we chose a budget-balanced billing system and since appliances are rescheduled to cheaper off-peak hours, utility energy costs are lower in Scenario 2 by 70%, 57%, 32%, and 65% compared to that in Scenario 1, for the days chosen across the four seasons, respectively.

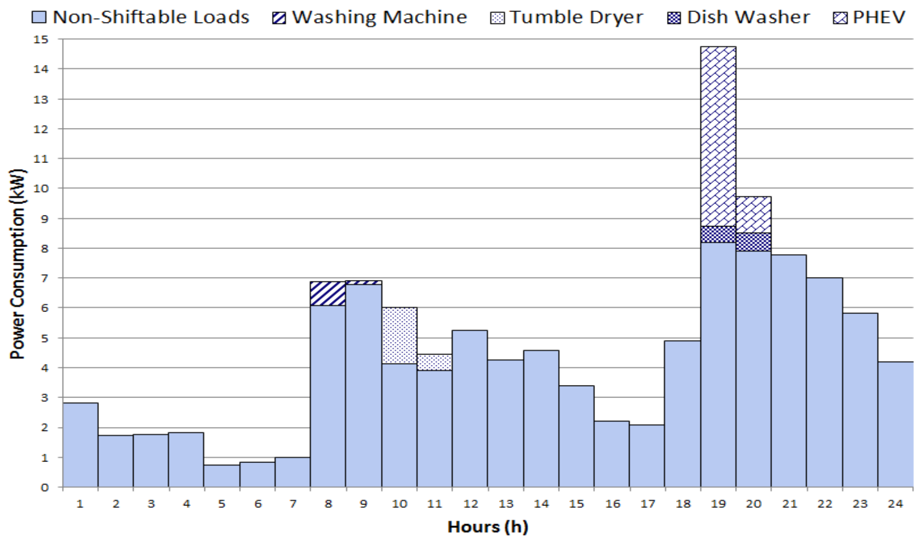

Fig. 2. Scenario 1: the unscheduled "shiftable" appliance loads of the consumer under investigation and the aggregate "non-shiftable" neighbourhood-level loads (December)
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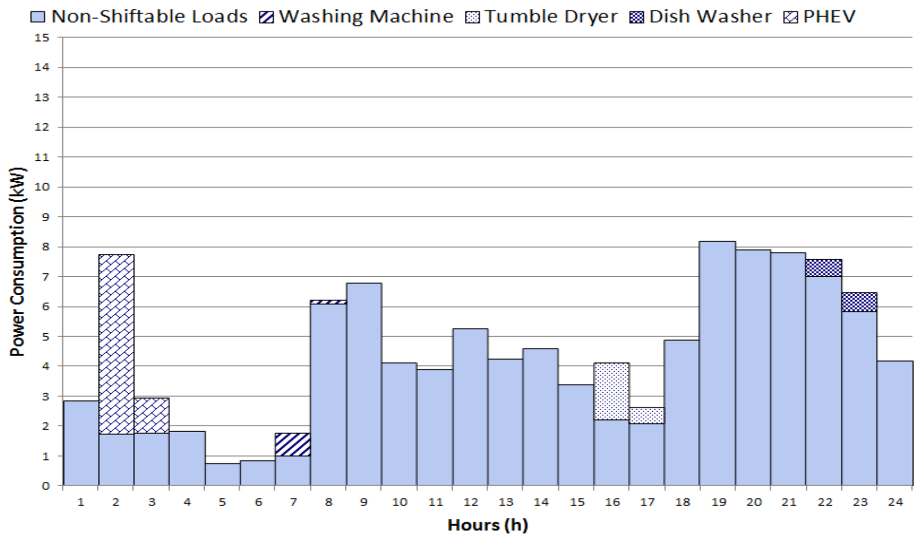

Fig. 3. Scenario 2: the scheduled "shiftable" appliance loads of the consumer under investigation and the aggregate "non-shiftable" neighbourhood-level loads (December)

6.3 Improved Load Factor

As the "shiftable" appliances of the household under investigation are rescheduled to operate during off-peak hours instead of peak hours, the load factor of the aggregate load in Scenario 2 is improved by 44%, 13%, 19%, and 28% compared to that in Scenario 1, for the days chosen across the four seasons, respectively. This indicates improved resource allocation in the power grid.

7 Conclusion

In this paper, we leverage the fair billing mechanism proposed by Baharlouei et al. [3] to evaluate the energy consumption scheduling game proposed by Mohsenian-Rad et al. [16]. We have implemented and evaluated a scheduler that optimally allocates the operation of "shiftable" appliances for a consumer based on his time preferences, the aggregate hourly "non-shiftable" load at the neighbourhood-level, and a fair billing mechanism. As the deployed billing mechanism takes advantage of cheaper off-peak electricity prices, we show that it helps in lowering utility energy costs and electricity bills, and improving the load factor of the aggregate neighbourhood-level power load. We also conclude that consumer flexibility in rescheduling appliances is rewarded fairly based on the shape of his power load profile rather than his total energy consumption.

8 Future Work

Eventually, we intend to investigate an appliance scheduler that coordinates electric energy consumption among a large number of households (agents).

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