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Demand-Side Management in Residential Community Energy System for the Smart Grid

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Doctoral Dissertation

Demand-Side Management in Residential Community Energy System for the Smart Grid

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Abstract

The electrical grid has operated on a centralized, top-down model for the past century and heavily relied on fossil fuels for energy production. Grid operators are responsible for the reliable delivery of electricity to consumers where electricity generation must be matched with the total demand at all times. The main driving costs and capacity requirements are the electricity demand that occurs during peak periods. These peaks in demand require utility companies to operate costly and inefficient generators. Moreover, a concern of climate change and greenhouse gas emission leads to an expected widespread demand-side adoption of distributed energy resources (DERs), including renewable energy. The higher penetration of renewable energy resources causes the challenges of the grid operators to exacerbate. The intermittent nature of renewable resources and uncoordinated operation of DERs substantially limit the ability of the supply adaptation to the fluctuating demand and reverse power flow. One of the foreseeable solutions is to manage how end-users consume their energy. Demand-side management (DSM) is a technique to exploit the flexibility in the demand-side and change the consumption pattern of the end-users such that demand profiles match better with the supply and thus lower energy costs.

In this dissertation, a DSM method for a residential community with high penetration of DER is presented. In the proposed DSM method, a local energy sharing scheme is incorporated into a price-based demand response to exploit the value of DER, benefiting both the utility company and its customers. On the one hand, the utility company can adopt the DSM method to motivate the customers to shift their energy consumption and production such that peak demand and export energy can be reduced. As a result, the aggregate consumption curve becomes more flat and smooth. Therefore, the utility company can lower energy costs from the costly peak-time energy procurement and mitigate the problem of reverse power flow. On the other hand, the customers will be incentivized from participating in DSM and motivated to share their energy locally. Thus, increasing their energy bill savings and self-consumption, which maximize the value of DER.

We define a procedure of DSM into three sequential processes: day-ahead consumption scheduling, consumption rescheduling, and energy billing. In the day-ahead consumption scheduling, we propose energy price functions to motivate users to plan their energy consumption and formulate an energy bill minimization problem for each user based on appliance specifications and preferences. Then, we present an iterative distributed algorithm to solve for optimal consumption schedules while preserving the privacy of the users.

Furthermore, we aim to improve the practicality aspect of the proposed DSM model by addressing the uncertainty of human behavior and energy billing fairness issues. We propose the consumption rescheduling algorithm to allow the users to change their preferences during operating periods and recalculate consumption schedules for the remaining time in order to avoid unnecessary costs. The energy billing mechanism with a penalty/reward system is proposed to fairly allocate any energy bill discrepancy to users based on their deviated consumption from the assigned schedules.

Simulation results indicate the effectiveness of the proposed DSM model in terms of peak demand and export energy reduction while maximizing the energy bill savings of the users. Simulation on the impact of battery, PV generation, and user participation in the system performance is carried out. Furthermore, the simulation results of the proposed consumption rescheduling algorithm show improved consumption profile of the community in response to the changing preferences of users. Finally, the results of the proposed energy billing mechanism show the fair allocation of energy bills to each user proportion to the amount of deviated consumption.

Keywords: Demand-Side Management, **Distributed Energy Resource**, **Energy Consumption Scheduling**, **Local Energy Sharing**, **Smart Grid**

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List of Abbreviations and Symbols

Abbreviations

AMI Advanced Metering Infrastructure

BS Bill Sharing

CEC Community Energy Coordinator

CPP Critical Peak Pricing

CREST Centre for Renewable Energy Systems Technology

DB Demand Bidding/Buyback

DER Distributed Energy Resource

DGP Dynamic Grid Pricing

DLC Direct Load Control

DR Demand Response

DSM Demand-Side Management

DSO Distribution System Operator

EDRP Emergency Demand Response Program

EV Electric Vehicle

FIT Feed-in-Tariff

HEMS Home Energy Management System

I/C Interruptible/Curtailable

ICT Information and Communication Technology

LDA Local Distribution Area

LES Simulation scenario where DSM is implemented. Users trade energy through the CEC and able to share energy locally. Dynamic of grid price is not incorporated in local energy market.

LES+DGP Simulation scenario where DSM is implemented. Users trade energy through the CEC and able to share energy locally. Dynamic of grid price is incorporated in local energy market.

LSE Load Serving Entity

MMR Mid-Market Rate

OTS Off-the-Shelf battery operation

P2G Peer-to-Grid

P2G+DGP Simulation scenario where DSM is implemented. Users trade energy directly to the utility company. DSM is implemented where grid energy price is depended on aggregate community consumption.

P2G+OTS Simulation scenario where users trade energy directly to the utility company and apply "off-the-shelf" battery control strategy. No DSM is implemented.

P2P Peer-to-Peer

PAR Peak-to-Average Ratio

PV Photovoltaic

RTP Real-Time Pricing

SDR Supply-Demand Ratio

SOC State-of-Charge

TD Transmission-Distribution

TOU Time-of-Use

TSO Transmission System Operator

Symbols

α_i Earliest time that flexible appliance i can start its operation

$\alpha_i^{'}$ New earliest time that flexible appliance i can start its operation

β_i Deadline time that flexible appliance i need to finish its operation

$\beta_i^{'}$ New deadline time that flexible appliance i need to finish its operation

$\Delta\hat{l}_n^h$ Sum of consumption deviation from rescheduling process for user n in time slot h

$\Delta\tilde{l}_n^h$ Sum of consumption deviation from sudden violation for user n in time slot h

ΔB^h Different between realized and expected community energy bill in time slot h

Δb_n Total energy bill difference of user n

ΔL^h Total community energy deviation in time slot h

Δl_n Total amount of deviated energy consumption of the user n

Δl_n^h Amount of energy deviation for user n in time slot h

Δl_{max}^h Maximum energy deviation among individual users in time slot h

η_c Charging efficiency of battery

η_d Discharging efficiency of battery

$\mathbf{z}_n$ Vector containing energy consumption of appliances and battery operation schedules for user n

$\mathcal{A}_n$ Set of flexible appliances for user n

$\mathcal{A}_m^{'}$ Set of rescheduling appliances for user m

$\mathcal{H}$ Scheduling window for demand-side management

$\mathcal{H}^{'}$ Remaining scheduling window for consumption rescheduling process

$\mathcal{M}$ Set of rescheduling users

$\mathcal{N}$ Set of users

$\mathcal{Z}_n$ Set of feasible energy consumption of the flexible appliances and battery operation for user n

$\mathcal{Z}_n^{'}$ Updated set of feasible energy consumption of the flexible appliances and battery operation for user n

Ω_n^h Reward factor for user n in time slot h

Θ_n^h Penalty factor for user n in time slot h

a^h Energy cost and price coefficient in time slot h

A_n Number of flexible appliance for user n

b^h Energy cost and price coefficient in time slot h

B_n Total daily energy bill for user n

b_n^h Energy bill for user n in time slot h

b_n^* Realized energy bill of user n

$b_{n,conv}$ Realized energy bill of user n

$b_{n,DA}$ Expected day-ahead energy bill of user n

$b_{n,prop}$ Proposed energy bill for user n

$b_{n,prop}^{h}$ Proposed energy bill for user n in time slot h

$b_{n,RL}^{h}$ Realized energy bill for user n in time slot h

B_{prop}^{h} Sum of proposed energy bills from all user in time slot h

B_{RL} Total community daily realized energy bill

B_{RL}^{h} Total community realized energy bill in time slot h

C^{h} Energy cost of the utility company in time slot h

d_{n}^{h} Total energy consumption for household appliances of user n in time slot h

E_{b}^{h} Total local energy demand in time slot h

E_{s}^{h} Total local energy supply in time slot h

$E_{b,-n}^{h}$ Sum of all users' buying energy demand except user n

$e_{b,n}^{h}$ Amount of buying energy for user n in time slot h

e_{i} Total daily energy requirement for flexible appliance i

$E_{s,-n}^{h}$ Sum of all users' selling energy surplus except user n

$e_{s,n}^{h}$ Amount of selling energy for user n in time slot h

F Fairness index

g_{n}^{h} PV generation of user n in time slot h

h Hour h

i i-th flexible appliance

L^{h} Aggregate energy consumption of the community in time slot h

l_{n}^{h} Net energy consumption of user $n \in \mathcal{N}$ in time slot h

L_{-n}^{h} Sum of all users' net energy consumption except user n in time slot h

$l_{n,RL}^{h}$ Actual load for user n in time slot h

m m-th rescheduling user

n n-th user

p_{l}^{h} Local electricity prices

$p_{g,b}^{h}$ Electricity price for users to buy electricity from the utility company (grid buying price)

$p_{g,s}^{h}$ Electricity price for users to sell electricity to the utility company (grid selling price)

$p_{l,b}^{h}$ Electricity price for users to buy electricity from the CEC (local buying price)

$p_{l,DA}^{h}$ Expected day-ahead local energy price in time slot h

$P_{l,RL}^{h}$ Realized local energy price in time slot h

$p_{l,s}^{h}$ Electricity price for users to sell electricity to the CEC (local selling price)

Q_{n} Battery capacity for user n

SDR^{h} Supply and demand ratio in time slot h

SOC_{n}^{0} Initial state of charge of battery for user n

SOC_{n}^{h} State of charge of battery for user n in time slot h

SOC_{n}^{max} Maximum stage of charge level of battery for user n

SOC_{n}^{min} Minimum stage of charge level of battery for user n

t Time that user request for consumption rescheduling

w Load deviation weight of sudden consumption violation

x_n^h Sum of energy consumption of all flexible appliance of user n in time slot h

$x_{n,0}^h$ Sum of energy consumption of all non-flexible appliance of user n in time slot h

$x_{n,i}^h$ Energy consumption for flexible appliance i of user n in time slot h

$x_{n,i}^{h,max}$ Maximum energy consumption for flexible appliance i of user n in time slot h

$x_{n,i}^{h,min}$ Minimum energy consumption for flexible appliance i of user n in time slot h

y_n^h Battery charging/discharging energy of user n in time slot h

y_n^{max} Maximum charging/discharging rate of battery for user n

Chapter 1

Introduction

1.1 World Energy Crisis

Human civilization has mainly relied on energy from fossil fuels to produce electricity in order to propel our society forward. With the rise of the global population and industrialization in developing countries, the global demand for energy has reached extraordinary levels. Burning coal, oil, and gas have been the primary reason behind the rising levels of greenhouse gases in the Earth's atmosphere, which is a leading contributor to climate change. To prevent environmental disasters, humanity needs to reduce its energy demand that relies on fossil fuel. Renewable energy resources, which are cleaner and emit less greenhouse gas emissions such as solar and wind energy, could provide an alternative for energy sources.

However, integrating these new energy sources into existing grids pose many challenges. One of the big challenges is the intermittent nature of energy production. Wind and solar energy are highly dependent on the weather and the time of day, and their production may not necessarily coincide with the peaks in demand. Since storing a large quantity of electricity is still impractical, shaping the demand to match the supply is another viable solution. By coordination between supply and demand sides, we can manage how the energy is consumed or produced more efficiently with cleaner energy resources.

In this dissertation, we are exploring a solution to manage energy usage from the demand-side with coordination from the supply in order to efficiently balance supply and demand, promote renewable energy resources, and limit the use of fossil fuel for a global sustainable energy practice.

1.2 Overview of the Electrical Grid Today

Before we go further into details, an introduction to the contemporary electrical grid is necessary. Since the electrical grid first started growing in earnest in the early 20th century, it has worked on a centralized, top-down model. The grid is divided into four main components: generation, transmission, distribution, and consumption. Power is generated at large-scale power plants, usually far from end-use customers, and fed into high-voltage transmission lines. After being carried over a long-distance, power is injected from the transmission system into local distribution areas (LDAs) via substations at transmission-distribution (TD) interfaces, where the voltage is step-down by transformers. Finally, power is carried along distribution wires in various directions to reach end-use consumers.

In general, the transmission network is managed by transmission system operators (TSOs) to ensure the reliability of the transmission grid. In some countries or regions, utility companies also own power plants and distribute electricity to their customers as load-serving entities (LSEs). Whereas in other areas, the gird operation has been restructured, separating distribution from the transmission. In restructured areas, distribution utilities do not own power plants and buy power from wholesale markets and resell it to their local customers in retail markets. The wholesale markets, where competing power generators selling their power, are administered by TSOs. The distribution utility companies are acted as distribution system operators (DSOs), responsible for the reliability of distribution networks and provide energy connection to end-users. The nature of electricity is that it cannot be stored (in large quantity) and have to be consumed instantaneously after being generated. Thus, utility operators need to balance supply and demand by generating electricity to meet demand at all times. The current electrical grid is designed through a vertically integrated electric utility structure and one-way power flow with the objective to serve the reliability of the grid by investing in the infrastructure to meet peak load conditions. Fig. 1.1 shows the overview structure of the electrical grid.

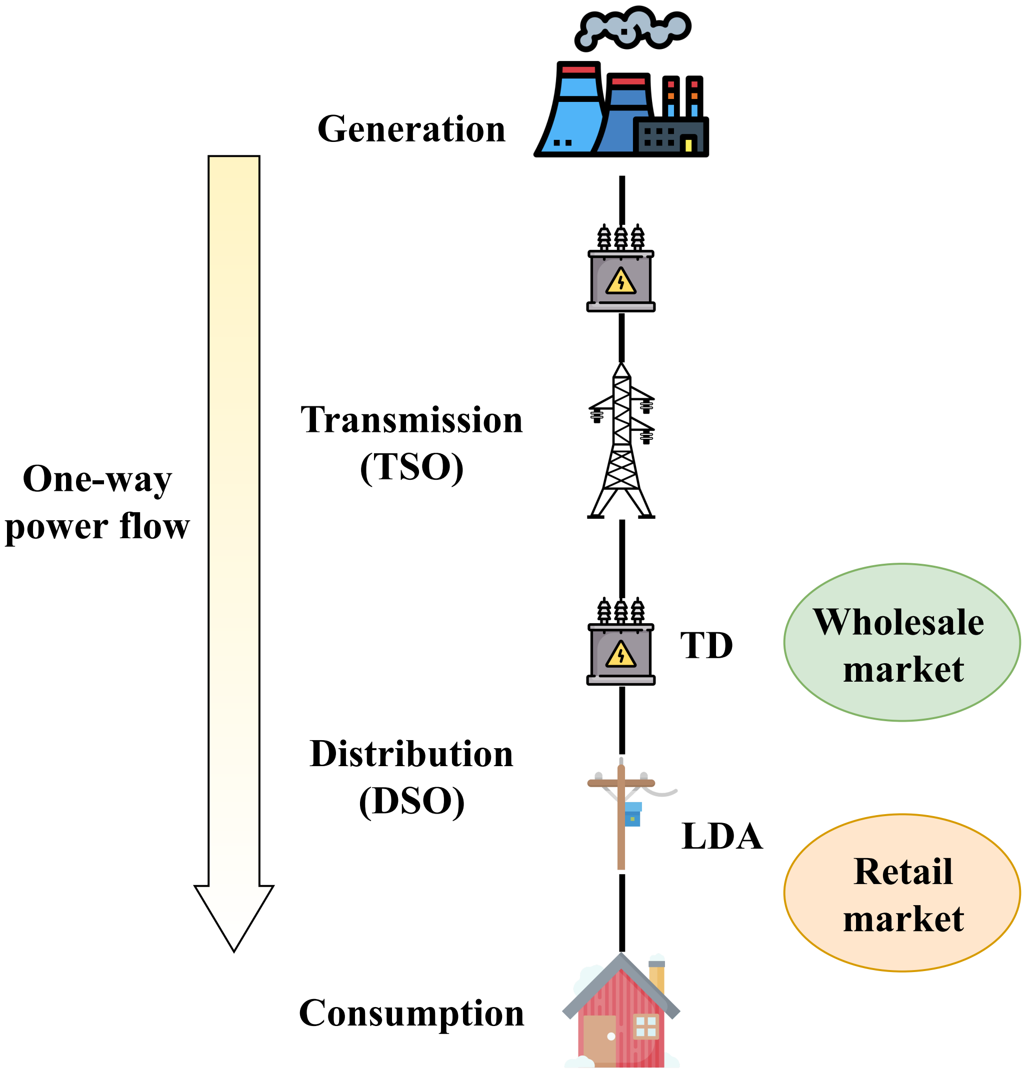

Figure 1.1: Overview of the conventional electrical grid.

As the technology progress and environmental concern, electrical grids around the world are in the state of significant transition toward the decentralization of electricity generation. Fig. 1.2 shows increasing trend in decentralization ratio of electricity generation by country around the world [1]. The rise of distributed energy resources (DERs) and renewable energy are the leading driving technologies. DERs can be referred to small-scale generation units that are located on the electricity end-users side, including solar PV system, battery storage, electric vehicles, and other resources such as load shifting. Over the past decade, there has been an acceleration of the infusion of the PV system, mainly due to the reduction in investment costs, advanced communication and control technologies, and environmental concern. Moreover, battery storage technologies and costs are catching up with the PV system and will be widely available in the consumer markets [1]. According to the Commonwealth Scientific and Industrial Research Organisation (CSIRO) [4], a grid-connected PV and battery storage system will produce electricity more cheaply than buying it from the grid in the near future. The Bloomberg New Energy Finance [5] estimates that by 2050, half of all residential buildings will have solar PV systems, and about one-third will also have battery storage.

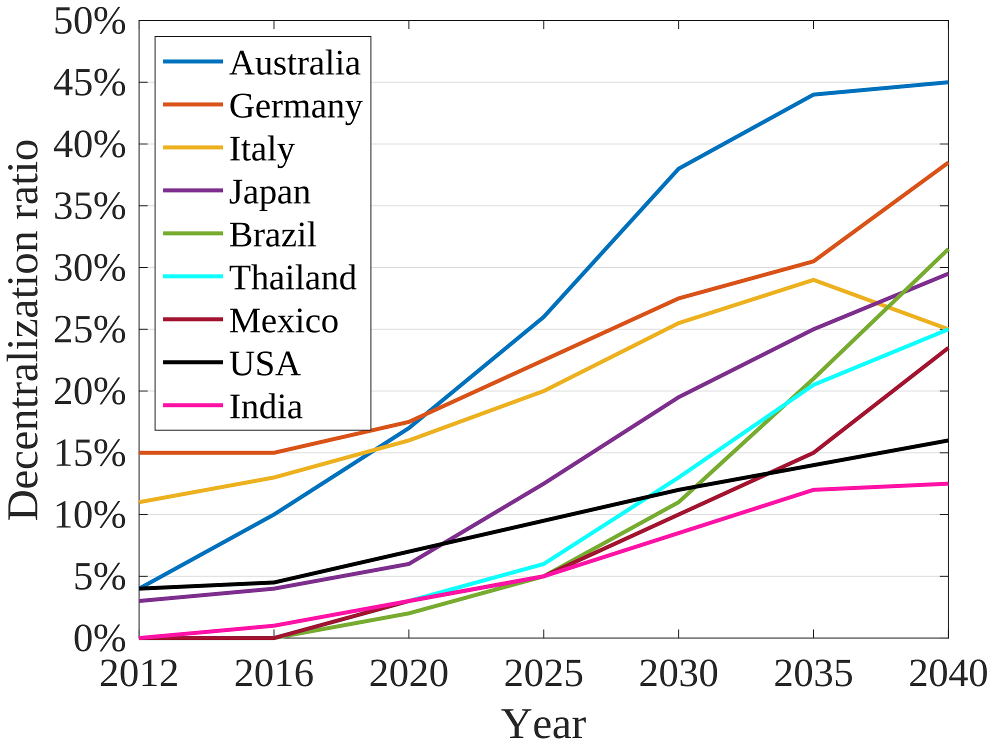

Figure 1.2: Decentralization ratio of electricity generation by country [1].

1.3 Challenges - Peak demand, Reverse Power Flow, the Duck Curve

In this section, we present some of the challenges that the grid operator is facing in the current electrical grid structure: matching peak demand, reverse power flow, and dispersion of consumption profile.

The electrical grid operators had only control over the supply. Since demand needs to be matched instantaneously, the grid needs to build with enough power plants to satisfy the highest possible peak in demand. However, most of the time, those costly "peak" power plants are not operating and idle since they operate only during peak consumption periods, which occur briefly. To meet the peak demand, the operators have to use those costly power plants. Since a marginal cost of generating electricity increases with the required demand, matching the peak demand increases the costs of the utility company. That is, ideally, the utility operator would desire for a constant, flat, and smooth demand curve in which they can achieve the most cost-effective power generation.

Furthermore, the rapid penetration of DER installation in the distribution networks poses technical challenges for the network operator, including voltage maintenance, reverse power flow, and lack of DER generation visibility. Although consumers benefit from having DER as it can reduce their electricity bills from self-consumption and/or become *prosumers* to sell surplus energy to their retailers or local utility companies to earn additional revenue in a feed-in-tariff (FIT) program [6], the aggregation of uncoordinated behavior of DERs could impact the net energy consumption that the network operator must serve. An example of DER's impact on a low-voltage distribution network consists of households equipped with PV systems is shown in Fig. 1.3. During day-time when PVs generate energy simultaneously, and there is not enough load to absorb all the generated energy, the surplus will be fed back to the network causing the voltage to rise and potentially overcome the maximum voltage limit of the network. Another example is when the operation of battery storage systems (act independently without coordination) could coincidentally inject energy with the time of high solar irradiance [7], which causes even more energy injection to the main distribution line and lead to violation of voltage and thermal limits.

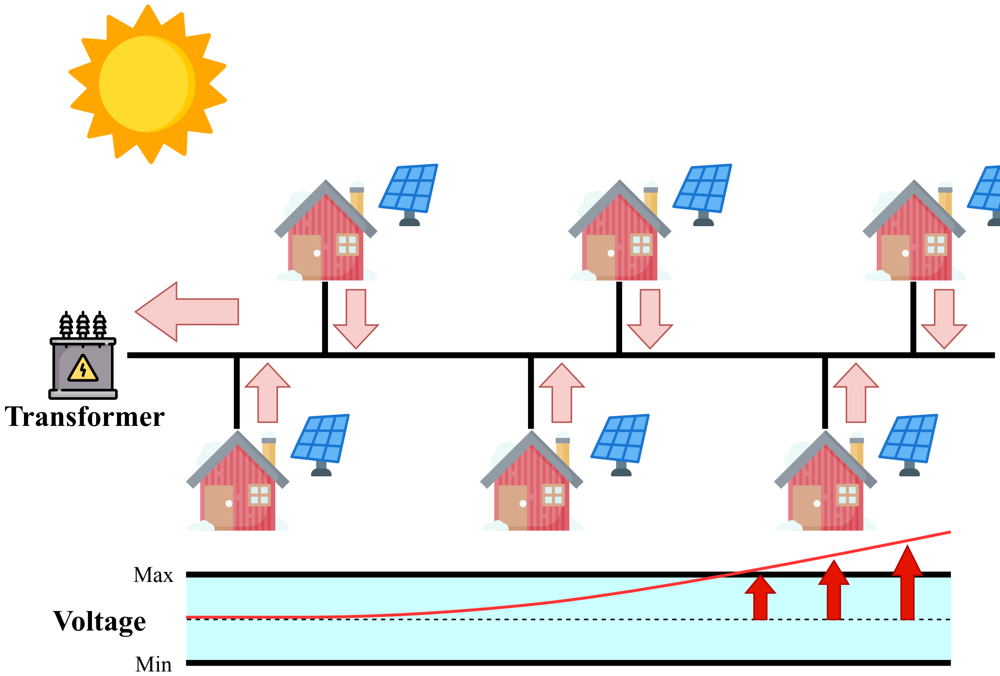

Figure 1.3: Solar PV injection into low-voltage distribution networks causing voltage rise problem

Both peak demand and over-generation PV create highly fluctuation in the consumption profiles. As reported by the California Independent System Operator (CAISO) [2], the net energy consumption could exhibit "The Duck Curve," (see figure 1.4) where a deep drop of demand appears in the mid-afternoon due to over-generation and quickly raises to the peak demand in the evening. This quick fluctuation of the consumption profile causes the operator a challenge to adjust the energy supply rapidly with more cost-expensive generators to meet the demand. Such operations are expensive and difficult to navigate.

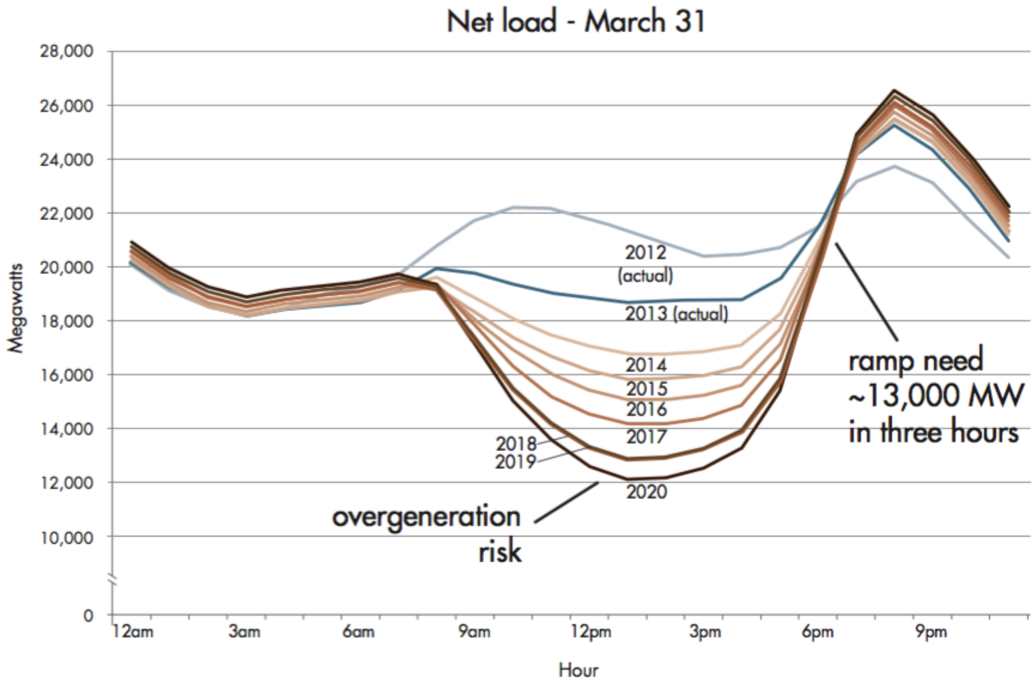

Figure 1.4: The duck curve of demand curve in California. (Figure source: CAISO [2])

The conventional solution used by distribution companies to manage the energy export of DER is to curtail or limit how much DER energy can be injected into the grid. However, the consumers lost financial benefits and letting clean, zero-carbon energy go to waste. Thus, decrease the value of DER. Upgrading current distribution infrastructures such as transformers, conductors, or feeding lines to expand the network capacity is also possible solutions. However, investing in new equipment and assets would only solve the issue in the short-term and not sustainable solutions. Besides, current power system management is only done in the supply-side of the electrical grid, whereas the end-use customers in the demand-side are considered passive and lack of participation in the management. The retail energy price used to bill customers is mostly a flat-tariff scheme. In this scheme, customers have no incentive to shift their consumption from peak-demand periods to off-peak demand periods.

Hence, based on the above challenges, coordinate energy management from both supply and demand sides is urgently required. If demand loads can be controlled, it can provide energy flexibility and an option for the grid operator to balance supply and demand more efficiently. Furthermore, a consideration of a more sophisticated active DER management method in the demand-side is needed to exploit the full potential value of DER while limiting physical threats pose on the grid.

1.4 The Grid of the Future

One of the foreseeable solutions is to revise the structure of the electrical grid and how it operates. A new paradigm of the electrical grid has emerged as “The smart grid”. The smart grid is a digitally enabled grid, facilitated by an advance in information and communication technology (ICT), smart meter, and home energy management system (HEMS), which can potentially overcome the existing limitation in the current electrical grid.

Instead of operating the electrical grid from a top-down one-way energy flow, a bottom-up two-way energy flow operation approach could be an alternative. With DER, end-use customers are seeking more control and choice over their energy uses and sources, as well as the societies, are becoming more concerned about environmental impacts and climate change. We can envision the future where DER can be managed from the demand-side to help smooth out the variations in demand and renewable energy production locally, with little supply from distant power plants. This would revise the electrical grid structure as the DSO could be the responsibility for balancing supply and demand within its LDAs by using flexibility from local DERs. Then, DSO presents the remaining aggregate supply or demand into a single virtual unit to the TSO through a TD interface. Thus, reduce operation complexity for the TSO. Fig. 1.5 shows a concept of the smart grid.

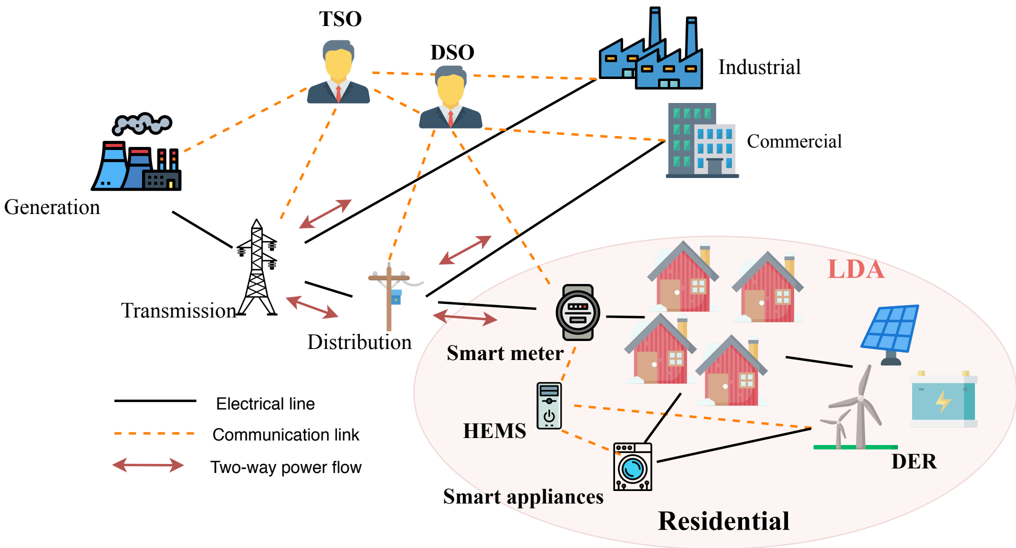

Figure 1.5: The smart grid

In order to shape the consumption demand, a demand-side management (DSM) program is one of the methods proposed for the smart grid to manage the consumption and production of the end-users in the demand-side of the electrical grid. Previously, DSM has focused on industrial and commercial consumers but, with an increasing number of DER, the residential end-user sector also gained attention from both academic and industrial. The price-based demand response (DR) method [8] is one of the DSM programs that the utility company employs an energy pricing strategy to encourage consumers to change their consumption behavior. Using different electricity prices at different times, the consumers can have incentives to shift their energy consumption from high price periods to low price periods. Thus, the design of energy price function and its character play an important role for the utility to achieve the desired consumer's response outcome.

1.5 Purpose of the Dissertation

The purpose of this dissertation is to develop a DSM method for a residential community with high penetration of DER to achieve *"win-win"* strategies for both the utility company and its customers. On the one hand, the utility company influences its customers to change their energy consumption pattern by adopting a dynamic energy pricing strategy such that aggregate peak demand and export energy of the community can be reduced. Therefore, the utility company can lower the energy cost from the costly peak-time energy procurement and mitigate the problem of reverse power flow. On the other hand, the users gain financial benefits from participating in DSM by providing flexibility from the demand-side. Based on the energy prices, the users can plan their energy consumption to minimize their energy bills. Also, the excess generation from DER can be shared among users through the local energy market, which is incentivized by local energy prices. Thus, increasing users' energy bill savings and self-consumption, which maximize the value of DER. Furthermore, we also consider improving the practicality aspect of the proposed DSM model by addressing the uncertainty of human behavior and energy billing fairness issues.

1.6 Structure of the Dissertation

The rest of the dissertation is organized as follows. Chapter 2 introduces the relevant background topics for the discussed research, which includes an overview of the smart grid, DSM, DR, and local energy sharing methods. Then, we present the motivations and objectives of our proposed DSM method.

In Chapter 3, the structure of the residential community energy system proposed in the dissertation is explained in detail, along with the definition and role of a utility company, a community energy coordinator, and residential users. Then, we introduce the process of the proposed DSM model.

Chapter 4 presents the day-ahead consumption scheduling, which includes the proposed energy pricing functions, local energy sharing mechanism, and energy bill minimization problem. An iterative distributed decision-making approach used to find optimal consumption schedules of all users in the community is described. The simulation results obtained are analyzed and discussed, and the impact of DER on the proposed system is demonstrated.

Chapter 5 presents the consumption rescheduling process to deal with an uncertainty of human behavior. The proposed rescheduling algorithm is described and evaluated by simulation. The results obtained are analyzed and discussed, demonstrating the impact of human behavior uncertainty and the effectiveness of the proposed algorithm.

Chapter 6 presents the proposed energy billing mechanism to address the fairness issue when consumption schedules are violated. The proposed penalty and reward factors are defined. Then, a billing function is presented for distributing any energy bill discrepancy fairly to all users. The simulation results are illustrated to confirm the feature of the proposed billing mechanism.

Chapter 7 presents a discussion of the proposed DSM model and its application in the future of the electrical grid.

Finally, Chapter 8 concludes the dissertation and suggests future work.

Chapter 2

Background and Literature Reviews

In this chapter, we present related background research topics, which include an overview of the smart grid, DSM, DR, and local energy sharing methods. Then, we describe limitations in the existing literature, leading to the motivations of the proposed DSM method. In the end, we summarize our research objectives.

2.1 Smart Grid and Demand-Side Management

The smart grid is a term that describes the modernization of the traditional electric grid that delivers electricity from energy sources to end-use customers. Various advancements in modern digital technologies reconstruct the traditional grid; it allows for two-way communication between the utility and its customers, real-time data monitoring and sensing along the transmission lines, and control automation [9]. Table 2.1 summarizes the main features of the smart grid.

Table 2.1: Comparison between traditional grid and smart grid

Traditional grid	Smart grid
One-way communication	Two-way communication
Centralized generation	Distributed generation
Passive consumers	Active prosumers
Limited number of sensors	Full grid sensor throughout
Manual restoration	Self-healing
Failures and power outages	Adaptive and islanded

In the residential sector, two critical enabling technologies are HEMS [10] and Advanced Metering Infrastructure (AMI) [11]. The application of HEMS is intended to automatically facilitate users in optimizing the use of household appliances and energy consumption. HEMS also equipped with the capability of data collection, data processing, data representation, and interaction with the user. With the installation of smart meter and AMI, information related to the cost of energy, energy usage, and grid status can be provided to the user from the utility company. This enhances the ability for HEMS to optimally control the use of electric devices, e.g., to reduce peak power and electricity bill.

DSM is one of the main feature technologies in the smart grid. Traditionally, utility companies design the electricity grid for peak demand rather than the average demand to achieve the high reliability required in power systems. This results in an under-utilization of the designed system. Improving the utilization in power grids become a crucial point due to the increasing demand for quantity and quality, limited energy resources, and costly to exploit new resources and built new generations. Also, new types of loads, such as electric vehicles (EVs) have emerged, which can potentially double the residential load. Expanding the generation to meet the increasing demand faces great concern regarding various environmental issues. For example, to meet the peak demand, oil and coal-fired power plants are widely used, which emit a large amount of carbon dioxide and other greenhouse gases. Thus, the development of DSM methods to manage the load in the demand-side has emerged as an alternative solution, instead of increasing supply to meet the demand. DSM has been invented and practiced since the 1980s by the Electric Power Research Institute (EPRI) [12] as a series of activities that utility companies initiate to change the user's load profile of energy consumption for maximizing benefit, delaying investment, and enhancing reliability. DSM is mainly categorized into two groups:

- Energy efficiency: A program in which promoting the reduction of energy requirement for the provision of services or products.

- Demand response: A program which defined by the US department of energy as

> "changes in electrical usage by end-use customers from their normal consumption patterns in response to changes in the price of electricity over time or to incentive payments designed to induce lower electricity use at times of high wholesale market prices or when system reliability is jeopardized" [13].

The energy efficiency programs are aiming for a long-term goal to reduce the amount of energy consumption by promoting the adaptation of a more efficient technology and production process. For example, switching to LED lighting, replacing old inefficient home appliances, or installing wall insulation for better indoor temperature control. Although this approach proved to be a cost-effective strategy, it requires long-term and wide-area of adaptation. On the other hand, the DR programs are focusing on a short-term strategy to change the consumption pattern of consumers. Utilities can implement and tailor DR strategy in order to achieve their designed system outcomes by the response from the demand. The detail of various types of DR programs is presented in the following section.

2.2 Demand Response

Among different techniques considered for DSM, the DR program is one of the most effective tools to shape the load profiles to improve the reliability and efficiency of the power grid. It can be considered as the means or tariffs that the utility company takes to incentivize users to change their energy usage patterns [14]. With the recent investment in smart grid technologies, especially the large roll-out installation of smart meters, the potentials of DR are fully exploited on a large scale, including a residential sector. DR programs are further categorized into two main branches: *incentive-based* and *price-based* programs. Summary of DR and DSM categories is shown in Fig. 2.1.

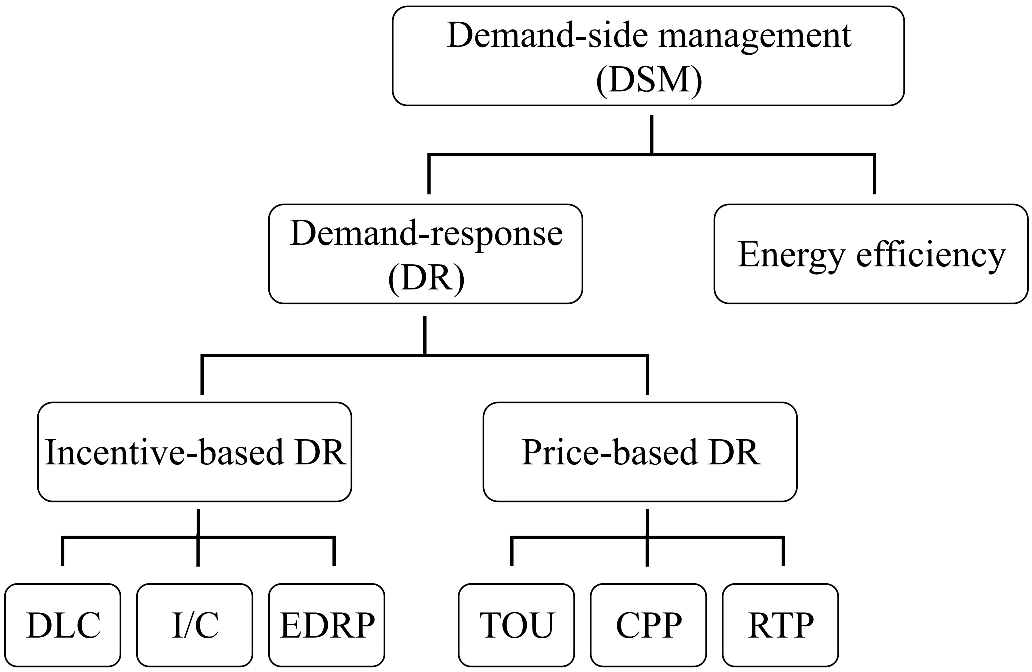

Figure 2.1: Categories of demand-side management programs

2.2.1 Incentive-based DR

In the incentive-based DR, an incentive is paid to the participating users for a reduction of demand. Based on an event, triggered by system congestion or peak load, the program provides load modification incentives to those users in addition to or separation from electricity payments. Example of program variations are listed as follows:

- Direct load control (DLC): In the DLC program, the utility company has permission from the participating users to remotely control specific electrical devices, e.g., air conditioner and water heater, whenever necessary. Based on agreements, incentive payments are provided for the demand reduction. Thus, the utility company can mitigate peak loads during high demand periods without the need for a more costly generation.

- Interruptible /Curtailable Service (I/C): In the I/C program, a discount or credit in electricity bill is provided to the participating users for agreeing to change energy consumption when necessary, such as during system contingencies.

- Demand bidding/buyback (DB): In the DB program, a specific price or reward is given to large customers for a specified amount of load reduction. This program is mainly offered to larger industrial customers or aggregated small-customers with a third party representing them for bidding.

- Emergency Demand Response Program (EDRP): In the EDRP program, a short-notice load reduction request is sent to the participating users during emergency events. The users receive incentive payments in reply to their load reductions.

Since the incentive is done through a contract with each individual customer, the incentive-based DR is more suitable for commercial and industrial power users where the amount of available demand flexibility is large. However, for residential users, due to the smaller consumption scale and a large number, dynamic energy tariff strategies are seen as a more suitable approach.

2.2.2 Price-based DR

In price-based DR, information on different electricity prices at a different time is provided to the participating users as an alternative to the legacy flat-rate tariffs. Based on the price information, users are motivated to use less electricity when prices are high and vice versa. Thus, the utility company can design the electricity prices such that peak demand can be reduced. In other words, opposed to the direct control method, the price-based DR can be seen as an indirect load control method that induces users to change their energy usage patterns according to the variance of electricity prices. To get maximum benefits of the price-based DR program, HEMS and automate device control are required to facilitate the load shifting of the users. Fig. 2.2 shows the conceptual design of price-based DR. Example of program variations are listed as follows:

- Time-of-Use (TOU) Pricing: The TOU pricing is an electricity rate plan, which varies according to the time of day, season, and type of day. Peak demand hours are subjected to higher prices, and off-peak demand hours are subjected to lower prices. This price structure provides price signals to energy users to shift energy consumption from peak hours to off-peak hours. Depending on the design, multiple pricing tiers can be implemented: on-peak, mid-peak, and off-peak [15]. In order to induce users to shift their loads over high-peak periods, high prices are imposed compared to off-peak prices. TOU pricing is usually determined and announce to the users in advance and keeps unchanged for an extended period of time [16–19].

- Critical peak pricing (CPP): The CPP is similar to the TOU pricing, except the high-peak price is replaced by an extremely high price. The CPP is only implemented on a small number of days in a year where the grid reliability is jeopardized, e.g., extreme hot or cold day during summer or winter. Outside of CPP duration, TOU pricing is typically employed [20–24].

- Real-time pricing (RTP): The RTP is also referred to as dynamic pricing, where the electricity prices vary at a different time on an hourly or sub-hourly basis. The price is adjusted based on the dynamic of the wholesale electricity market and intended to convey the actual generation cost to the end-user. The RTP usually announces on a day-ahead or hour-ahead basis. It has been widely considered more efficient than other price-based DR programs [8, 25–32].

The implementation of the price-based DR is to announce energy prices to the target customers in advance. The users then plan for their energy consumption, usually day-ahead, to respond to different prices at different times. Once the energy consumption plan is determined, the utility can determine its energy dispatch with more cost-efficient from the flatter demand curve. Literature related to the price-based DR is presented in the following section.

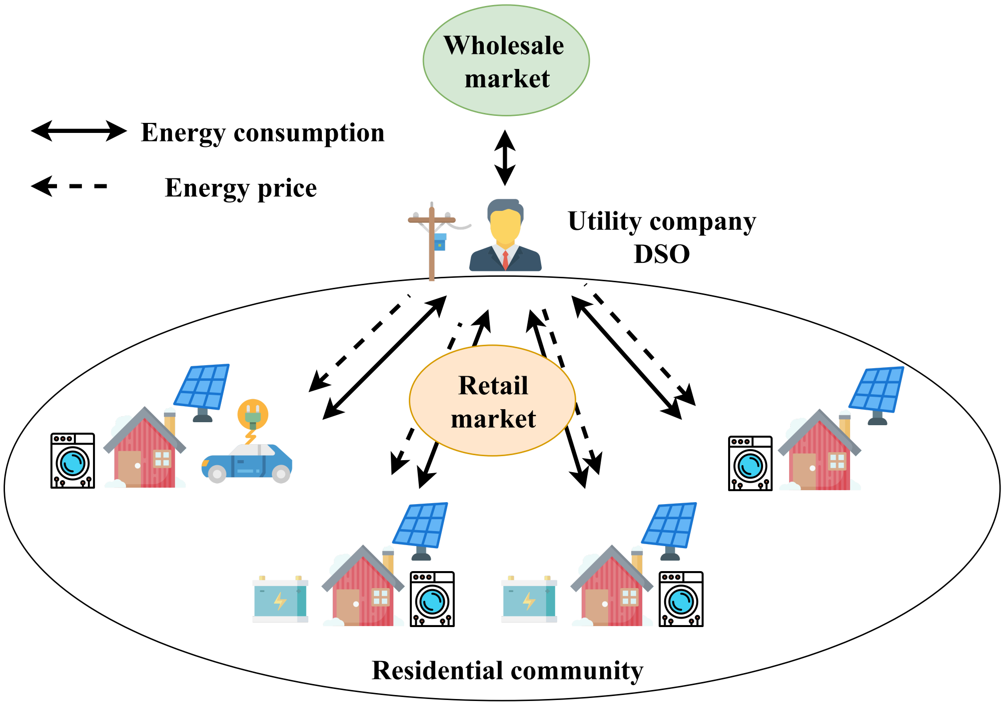

Figure 2.2: Conceptual design of price-based DR.

2.2.3 Price-based DR - Literature Review

Time-varying price structures in price-based DR are designed with the aim of shifting the timing of energy consumption so that peak demand is reduced. The ability to shift demand depends on the type of users and the corresponding load specification. According to the Smart Energy Demand Coalition (SEDC), residential DR relies mainly on price-based DR while industrial and commercial sectors are primarily subjected to incentive-based DR [33].

Various TOU and CPP residential DR pricing strategies have been studied in the early literature [14, 16–24, 34–36]. They commonly designed the price strategy to exploit the flexibility of the demand-side end-users by providing them particular energy price signals in order to achieve some desired outcomes, e.g., reducing energy cost and production, lower peak demand, and flattening the demand curves. Although TOU and CPP pricing schemes show benefits to the overall power system, they cannot reflect variations of the prices in the wholesale market in real-time, and thus are unable to effectively incentivize customers to lower their energy usages during peak-demand periods or to shift their energy usages from high-demand periods to low-demand periods. RTP is an effective solution to the above problem.

RTP schemes have been considered in [8, 26–31], where the energy price strategies are commonly related to the generation cost of the utility company. This generation cost is usually formulated to reflect the dynamic of the wholesale market. The results of RTP schemes show a better response from the customers in terms of peak and energy cost reduction as well as economic benefits improvement for an individual user, compare to less dynamic TOU and CPP schemes.

Some existing works in the literature also considered the context of high penetration of DER in price-based DR schemes [37–44]. In [37], a day-ahead optimization is formulated to minimize the cumulative monetary expense of each active user on the demand-side by the scheduling of distributed energy production and storage. A dispatch strategy of shared battery storage between customers and distribution network operators was proposed in [38] to effectively respond to energy prices and network conditions. Authors in [39] presented a game-theoretic approach analysis for interaction between users and the utility in the presence of storage with selling-back to grid option. In [40], an energy management scheme was carried out to minimize total energy cost to the central power station while maximizing user benefits using the proposed utility and cost models with DERs. In [41], energy consumption and storage optimization problem was formulated to minimize the load deviation from the average demand over the consideration scheduling horizon. Centralized and distributed algorithms were proposed to solve scheduling problems. The DR scheme with an aggregator was proposed in [42] to schedule dynamic loads influenced by real-time pricing. The outcomes show a great reduction in PAR and overall energy cost compared to other different pricing scenarios. In [43], a peak power-limiting DR scheme was proposed for scheduling controllable loads, storage, and generation to meet the demand of households in a dynamic pricing environment. However, the option for selling energy back to the grid was omitted. A DSM scheme in [44] was proposed with an option for the users to sell excess energy back to the grid, considering energy cost minimization and comfort maximization in a distributed manner.

Consideration of uncertainty in the DR system is discussed in [32, 45–48]. In [45], the DR program is studied in the presence of an uncertain supply of renewable energy. An online-DR algorithm is proposed to maximize the social welfare over two timescales: day-ahead and real-time. The optimization problem is formulated as a dynamic program and solved by a distributed heuristic algorithm. The simulation results show the performance and impact of renewable energy on the maximum social welfare. The uncertainty of renewable energy sources is considered in the supply side in [46]. Power available from the renewable is modeled using a discrete-time Markov chain. With knowledge of the steady-state probabilities and, users can compute consumption schedules and choose an energy supplier to minimize their energy costs. The results confirm cost reduction from the proposed DSM by selecting an energy supplier and shifting of appliances. In [48], forecasting error of renewable generations is considered in microgrids. A two-stage real-time algorithm is proposed using dynamic optimization to compensate for the uncertainties. Numerical simulation results show the proposed method performs better than other existing methods when dealing with the uncertainties in terms of economic benefit and netload characteristics. In [47], the uncertainty of renewable energy resources is handled via information gap decision theory to reduce undesirable costs with maximum tolerable a given worse-case procurement cost due to generation uncertainty. The simulation results show that the proposed method can reduce the impact of renewable energy source uncertainty on the energy cost. In [32], forecast error in load and generation is addressed. The author proposed a real-time DR scheme to update the forecast values and recalculate the consumption schedule of every user in each hour during the operation day. This process required all users to re-adjust their schedules to compensate for the forecast error. The results showed better cost saving compared to a day-ahead scheduling scheme, which suffered from the forecast error.

Another interesting aspect in DR is Fairness. While many works in DR can achieve system optimality, they need contribution from all participants. To encourage users to continue their contribution in the program, a proper design of the system fairness must be done. Various fairness criterion in DR has been considered in [49–60]. In [49], a fair pricing model is proposed by considering the various type of fairness criteria such as type of user, appliance category, and income level. Although the results showed improvement in fairness level, detailed information of users might be difficult to access in order to compute the energy bill in practice. In [50], a billing mechanism is proposed to fairly bill the users by considering the load flexibility of each user. The billing rewards to the users with a more flexible load by taking into account the exact shape of users' load profiles. The results showed improvement in the fairness level in the DSM system. Later, the same author extends her work in [51, 52] to address the trade-off between system fairness and optimality. An alternative fair billing mechanism using the concept of Shapley value is proposed to allocate energy costs across the users based on their contribution to minimizing the total cost of the system. They concluded that there is a trade-off between improving the fairness level and achieving an optimal solution. Fairness consideration of the user's discomfort was studied in [53]. They showed that when load-adjustment and load-shifting become more effective, discomfort level increases and leads to a system with unfairness. Again, they also observed a performance trade-off in the design of DR programs. Authors in [54, 55] also considered fairness using the Shapley value in their proposed billing mechanism. Both works used a sampling-based approach that approximates the Shapley value. The results showed better savings, flattening the load, and avoids peaks while maintaining fairness level. In [56], a billing mechanism is proposed to fairly compensate a group of residential consumers who collectively reduce demand during a load curtailment event. A weighted voting game and the Shapley value are used to assess the fairness among users. The impact of the power loss and the voltage deviation from each participating user is considered as a fairness measurement in [57]. In [58], the authors proposed a fairness index to compare the existing billing mechanisms in the literature. They claimed that a fair mechanism should reflect the cost user induces to the system. Works in [59,60] considered improving fairness level in energy billing when the user's actual consumption is different from the assigned schedules. A penalty is given to each user based on the amount of deviated consumption. However, they did not take into account the possibility when consumption decreases from the assigned level. That is when including DER in the system, consumption deviation can occur in both directions; upward and downward.

2.3 Local Energy Sharing

The recent developments of the smart grid have opened an opportunity for consumers to become more active players in the power system, instead of being passive energy end-users. The new active users can participate in the energy generation and consumption process by utilizing their local energy resources, managing their demand, and communicating with other users. Although a high penetration of DER in the distribution networks could cause network management issues, DER offers many potential benefits to the end-users. Recently, an idea of local utilization of DER has emerged as *local energy sharing*, where excess generation from DER can be shared among prosumers, instead of only exporting back to the grid [61]. This energy sharing needs a local market to manage transactions among different users. Local energy sharing can be classified into two categories based on the interaction of the market players: *full peer-to-peer* and *energy sharing through a mediator*:

- Peer-to-peer (P2P): In the P2P market, all participating users directly interact with each other to sell or buy energy. Users can negotiate their preferred energy price and amount of trading energy. There is no need for an intermediary entity.

- Energy sharing through a mediator: In this case, a third-party entity is presented as an intermediary interface between energy buyers and sellers. It manages energy transactions on behalf of all participating users and allocates energy from sellers to buyers. The market rules and energy pricing also set up by the mediator.

Fig. 2.3 shows a simple example to illustrate the full P2P and mediator-based energy sharing classification.

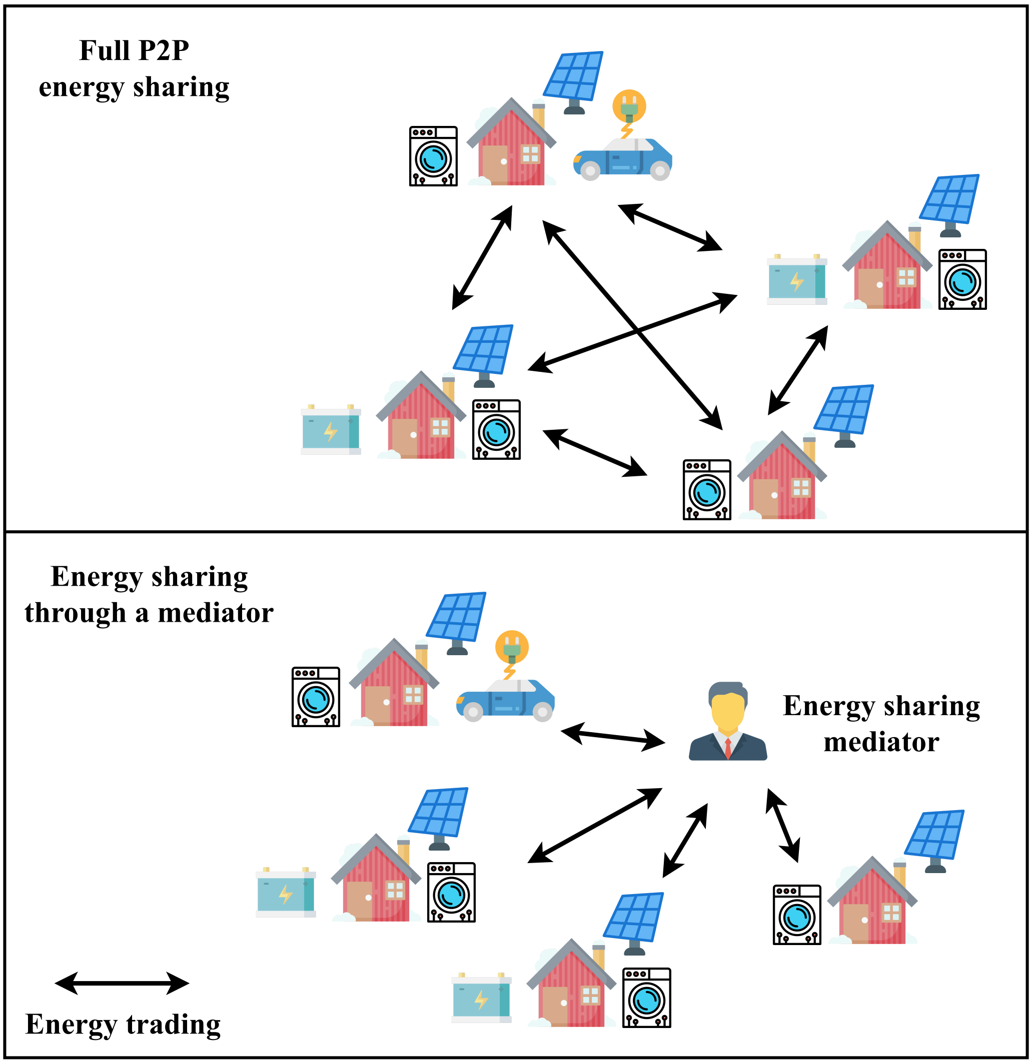

Figure 2.3: Full P2P and mediator-based energy sharing designs.

Although the full P2P local energy sharing market shows great potential in utilizing DER to its full value, advanced communication networks and technologies are required to sustain the market designs. Blockchain technology can be the key factor in deploying a P2P market in the energy sector [62–64]. However, with complexity involving the negotiation process and transaction of energy from all peers, it is expected that the energy sharing through a mediator or a platform would be the intermediate step toward the full P2P markets [65]. Thus, in this research, we focus on the local energy sharing with a mediator, which has the potential to be realized in the near future. Literature related to local energy sharing with a mediator is presented in the following section.

2.3.1 Local Energy Sharing - Literature Review

Recent local energy sharing schemes with mediators have been presented in the literature [66–78]. In [66], a joint load scheduling and power trading was proposed. The users with excess generation offer their surplus and determine selling prices in order to maximize their revenues. The results showed a reduction in energy cost and reverse power flows. A local energy sharing scheme facilitated by an intermediate entity was proposed in [67] to manage the energy sharing inside a community. Internal sharing prices are calculated using the ratio of local supply and demand. The users schedule their loads to maximize bill saving. The proposed system achieved cost saving compared to the FIT scheme, where users can only sell the surplus to the grid. Maximizing the profit of a microgrid operator while considering the user's utility in local energy sharing microgrid was considered in [68]. The results confirmed that the profit of the operator and the utility of the users increased by coordinating the energy sharing between users. In [69], a discriminate energy sharing price model was proposed to maximize the sum benefits of users while ensuring fairness among them. In the proposed system, the users sell surplus energy to a shared facility controller inside the community, and a cake cutting game has been proposed to calculate the energy prices. The results showed a better total monetary benefit of the users compared to the FIT scheme. In [70], a distributed community-based market framework was proposed to allow users to actively optimize their DER sharing. A third-party node, e.g., community manager, was introduced to influence the users' energy dispatch decision as well as revenue and payments. Various possibilities of community objectives and fairness measures are presented using the proposed market framework. In [71], the centralized control strategy of battery storage and local energy pricing model was proposed to maximize the economic benefits of the community. Individual users' bill saving was ensured using a compensate pricing strategy. A mid-market rate based energy pricing scheme was proposed in [72]. The proposed energy trading scheme, inspired by a canonical coalition game, achieved sustainable participation of active users with guarantee cost-saving benefits. In [73], the benefit of energy storage in the local electricity market is presented with two different setups: decentralize and centralized storage. Improvement in savings for the users can be achieved by the proposed market designs compared to the case without local energy trading. Performance comparison of three different energy sharing mechanisms was carried out in [74]: supply and demand ratio (SDR), mid-market rate (MMR), and bill sharing (BS). The results showed that all local energy sharing schemes have the potential for improving both economic and technical benefits. The SDR mechanism outperforms other mechanisms in overall performance. In [75], a local energy sharing market was proposed to integrate prosumer communities into the day-ahead and intraday market operations. A two-stage stochastic programming approach was developed for a decision-making process under the uncertainty of generation and prices. The results showed a significant decrease in electricity bills for the users while increasing the community's self-sufficiency. A concept of multi-class energy management in energy trading has been presented in [76], which treat energy as a heterogeneous product accounting for individual prosumer energy preferences. The proposed energy market platform coordinates energy trading between prosumers and the wholesale electricity market to minimize the cost associated with losses and battery depreciation. In [77], an energy trading among prosumers in a community was proposed as a game-theoretic model. The trading process consists of two separate competitions: seller's price competition and selection of seller among buyers. The results showed that significant financial and technical benefits to the community could be achieved from DER. Technical constraints of the network were considered in [78] under the proposed energy trading scheme. The proposed method ensures that no network constraint is violated during energy sharing transactions among prosumers. The results confirm the economic benefits of the users while keeping the network under the limits comparing to other curtailment methods.

2.4 Research Motivations and Objectives

In this section, we will discuss the limitations of the existing literature and highlight our research motivations and objectives.

In order to design a DSM method for high penetration of DER in the residential community, proper designs of energy price functions and interaction among entities are required. Despite the aforementioned work have provided valuable methods and results, there are still notable gaps in the existing literature in terms of DR pricing function: Firstly, the existing research has failed to design the price signal to encourage the use of DER and mainly focused on the aggregate energy consumption profiles. Secondly, the full potential value of generated DER energy is still yet to exploit. In most of the price-based DR works, the surplus energy is exported back to the grid or being limited to export to prevent from damaging the power network. Therefore, the benefit to the user owning DER is reduced. Noticing these shortcomings, the first motivation in our research is to design a DSM model that taking into account various types of DER and exploiting the possibility of managing the generated DER energy more efficiently.

On the other hand, inspired by the works in local energy sharing research, we notice the potential to share the DER energy locally and leverage the benefit of DER. The design of local energy markets in the existing literature mainly focused on the dynamic of local supply and demand and incentivized the users to share their DER surplus. However, they have failed to consider the possibility of interacting with the utility company and ignored the outcome of the community consumption profiles. Without the dynamic of grid conditions, the local energy market could influence the user's consumption behavior in an undesirable way, e.g., peak consumption during high-demand periods. Hence, our second motivation for designing the DSM model is to consider the interaction of the utility company in a local energy market mechanism. Thus, combining the first and second motivations inspire us to incorporate local energy sharing mechanism with the price-based DR and propose local energy price functions that depend on the dynamic of both grid condition and local DER. We aim to encourage users to change their consumption patterns to align with the system objectives, e.g., reducing peak demand and export energy, while maximizing energy bill savings of the users by sharing energy locally.

Furthermore, since the DSM methods commonly consider energy consumption planning ahead of time, e.g., day-ahead scheduling, various type of uncertainty can cause the realized consumption to be different from the expected consumption plan, resulting in compromised outcomes. The most common uncertainty consideration is a forecast error in renewable generation, e.g., PV and wind energy. The existing literature has proposed various methods to address the issue, including real-time recalculation of the consumption schedules during the operation periods. However, we notice a lack of consideration in the existing research on user behavior uncertainty. While the production of renewable energy resources can be predicted with high accuracy in short periods, the behavior of users could be difficult to predict [79]. To cope with such uncertainty, we propose a consumption rescheduling algorithm to allow users to request for change and recalculate the consumption schedule in order to minimize the impact of the uncertainty to the overall system and their bill savings. Different from the existing approaches, our consumption rescheduling algorithm only allows the user who changes his preference to recalculate the consumption schedule while other users kept their assigned schedule unaffected, preventing from frequent schedule alternation.

Finally, to have an effective DSM program, consideration of improving fairness also an important aspect. A DSM program which treats the participating users fairly would be able to maintain active participation and able to exploit the available flexibility to its full capacity, while the program with lack of fairness could discourage the users from participating in the DSM activity and possibly opt-out from the program. As the above-mentioned works related to fairness in price-based DR, fair allocation of energy cost (or energy billing) to all users based on specific fairness criteria is a common approach. Considering the existing fairness criteria, we notice that the realized energy consumption could deviate from the optimal assigned schedules and cause unfair billing to users in the community. Thus, we further propose an alternative fair billing mechanism in our DSM model. Since we considered the residential community with high penetration of DER, where energy consumption could deviate in both upward and downward directions, the existing fair billing mechanisms are not applicable to our system. Thus, to fairly address any billing discrepancy, we introduce penalty and reward factors based on the user's violation and commitment in our proposed billing mechanism.

The objectives of this dissertation can be summarized as follows:

- To design a residential community energy structure with local energy sharing for DSM which incorporates a local energy market with the price-based DR to efficiently manage the energy consumption of a residential community that consists of high DER penetration.
- To propose a dynamic price model for DSM that can motivate users to better utilize energy from DERs and provide demand-side flexibility such that peak demand and export energy of the community are reduced while maximizing the energy bill saving of the users.
- To develop a consumption rescheduling algorithm in DSM that can reduce the impact of uncertainty due to human behavior even in the case of last-minute preference changes, such that demand peaks and unnecessary energy costs are avoided.
- To design a billing mechanism that can achieve fair energy billing in DSM where an impact of rescheduling users and consumption violations are taken into account when distributing the energy bill to all users based on their individual action.

2.5 Chapter Summary

In this chapter, we introduced the background of the smart grid and two of the main technologies: DSM and local energy sharing. We explained the potential of the price-based DR method to influence the users to change their energy consumption patterns. We highlighted that, with high penetration of DER in the demand-side, the existing price-based DR method in the literature still lacks consideration to exploit the value of DER to its full potential. On the other hand, we also explained the potential of local energy sharing among users to maximize the benefit of DER. We focused on the energy sharing scheme with a mediator, which could be possible to implement in the near future. We also highlighted the research gap of the existing local energy sharing schemes in the literature, which did not consider the interaction between the utility company and its users in the energy sharing community. Those aforementioned limitations and research gaps inspire us to propose a DSM method, which incorporates price-based DR and local energy sharing. We proposed a local energy market to exploit the full potential value of DER, where local energy prices are influenced by local energy supply and demand, as well as the aggregate energy consumption profile of the community. Thus, our proposed DSM method aims to encourage the users to shift their energy consumption to align with the utility objectives (reducing peak demand and export energy) while benefit from energy bill savings. Furthermore, we explained how human uncertainty and billing fairness could have a negative impact on the performance of the DSM and proposed methods to address the issues.

Chapter 3

Residential community energy structure

In this chapter, we present an energy system overview of a residential community and the proposed DSM model. Two main entities are presented, the utility company and the residential community, which is the set of users[1] plus an energy coordinator. In our system, the utility company provides energy to the users through the coordinator. First, we explain the residential community. Second, we describe the model of residential user's energy consumption and their DER. Third, we introduce the DSM model and explain the role and interaction among the utility company, the energy coordinator, and its users. Finally, we present a procedure of our proposed DSM, which consists of day-ahead consumption scheduling, consumption rescheduling, and billing process at the end of this chapter.

3.1 Residential Community Energy System

Consider a residential community composed of a set of users $\mathcal{N}$ receiving energy service from a single utility company. The utility company participates in wholesale markets to purchase electricity from generators and then sell it to the users in the retail market.

[1] The word "users" represents energy end-users, including consumers or prosumers, interchangeably

The residential community comprises of heterogeneous users $n \in \mathcal{N}$ with different demand and generation. Each user is equipped with a smart meter and a HEMS, which provide two-way communication among all entities and can automatically schedule and control the operation of electric devices based on the user's preference. We assumed that each user may own some types of DERs (PV panels, battery storage or load shifting capability). DER can be classified into two categories: *passive* or *active DERs*. An example of passive DER is a rooftop PV, where its production can be forecast with a high degree of confidence but controlling solar output is limited to a local algorithm and not being remotely controlled by a third party. An active DER incorporates external control inputs or data feeds that are being used to actively manage its behavior in response to price signals or other conditions. Examples of active DERs include household battery storage and shiftable load appliances. The residential properties are located in the same proximity, such that the PV generation patterns among them are correlated. However, since each user has different consumption patterns, the net energy consumption varies widely among users and thus, DER energy is possible to be shared inside the community.

To facilitate local energy sharing, we introduce an entity called *Community Energy Coordinator* (CEC). The CEC act as an agent representing the whole community, trading energy with the utility company on behalf of the users, and in charge of the local community energy market.

Time in a day is divided into equal-length slot $h \in \mathcal{H} = [1, ..., H]$ over the operation period, e.g. $H = 24$ hours in this work. Fig. 3.1 shows a concept of residential community in our proposed DSM model.

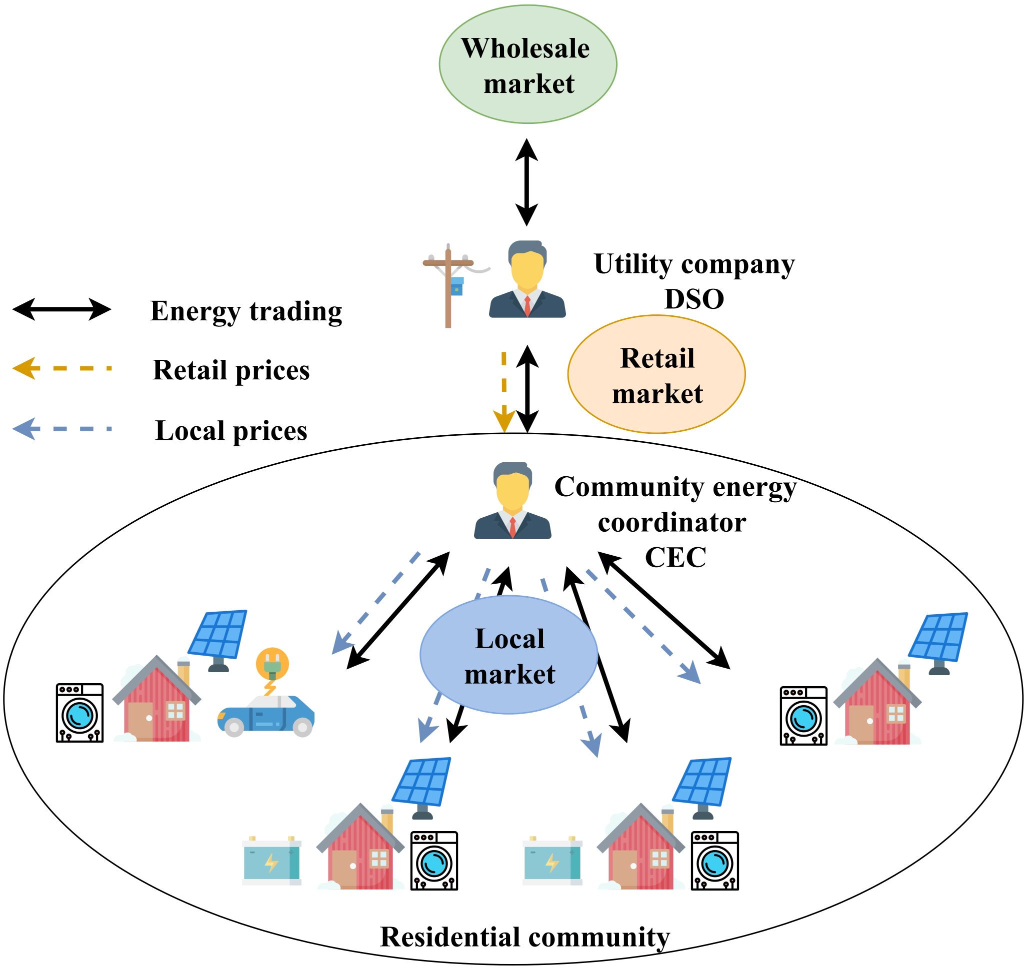

Figure 3.1: A residential community energy system for the proposed DSM.

3.2 Residential User Model

In this section, a residential user model is presented. Let l_n^h denotes a net energy consumption of user $n \in \mathcal{N}$ in time slot h. Then, depending on l_n^h, a user can be classified into one of the two roles: *a buyer* or *a seller*. The user is a buyer if the demand cannot be satisfied by self-generated energy or by discharging from a battery ($l_n^h \geq 0$) and thus extra energy needs to be purchased. On the other hand, the user is a seller if the demand can be fulfilled by local energy sources ($l_n^h < 0$) and has surplus energy to be sold. Self-generated energy from PV is prioritized for self-consumption. Then, a surplus of locally generated energy, if any, is sold to neighbors or the utility company through the CEC.

The users also schedule their appliances' energy consumption and the charging/discharging of a battery H hours in advance, using energy price and community consumption information provided by the CEC. The result of this scheduling determines whether a user is a buyer or a seller at any given time, resulting in the corresponding offers to sell or requests to buy energy to the CEC.

An energy consumption profile of a user can be described as a collection of electric devices' consumption behavior and constraints: household appliances, PV system, and battery storage. Fig. 3.2 illustrates an example of a household with DERs. The mathematical model of each of the electric devices and the user's net energy consumption are defined as follows:

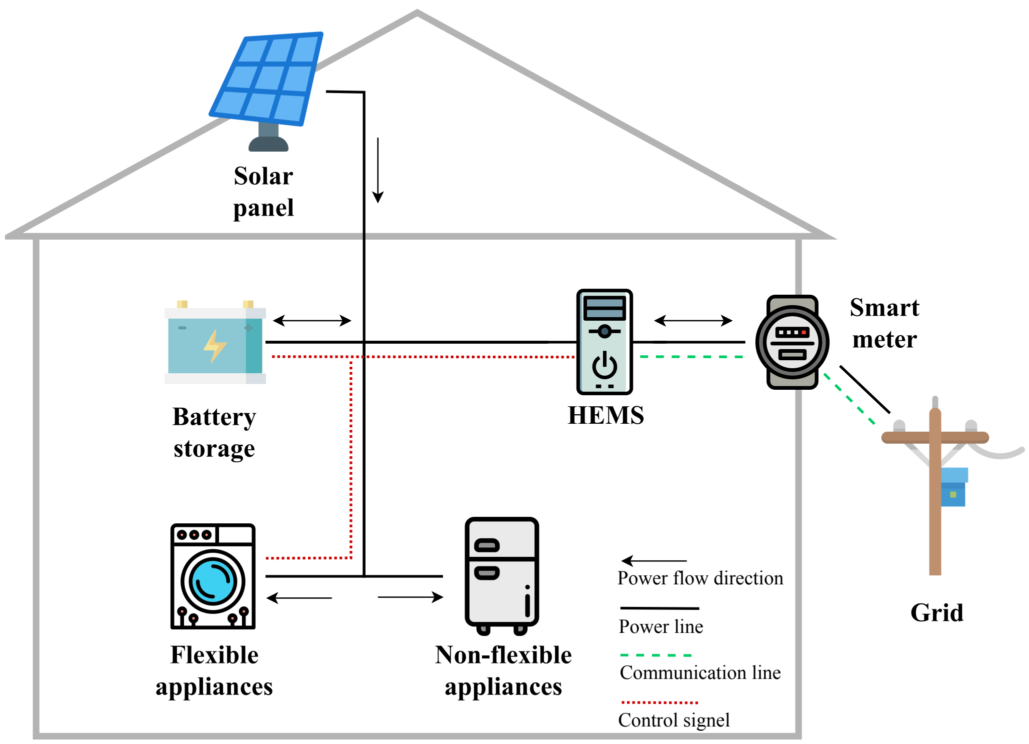

Figure 3.2: A typical household with HEMS and DERs.

3.2.1 Household Appliances

Each residential user has a number of appliances which can be classified into two types: *flexible* and *non-flexible*:

- Non-flexible appliance: Appliances in which their operation schedule cannot be shifted. The appliance consumption profiles are kept the same as their original schedules, representing a user's base energy consumption. Examples of such appliances are a refrigerator, a freezer, a lighting device, etc.

- Flexible appliance: Appliances in which their operation time can be shifted from the original schedules, respected to the user's preference operating time slots and daily energy requirement. The flexible appliance also considered as an *active DER* of the user. Examples of such appliances are a washing machine, a vacuum cleaner, dishwasher, etc.

We suppose that each user $n \in \mathcal{N}$ has a set of flexible appliances $\mathcal{A}_n$, where $A_n = |\mathcal{A}_n|$ is the number of flexible appliances. For each flexible appliance $i \in \mathcal{A}_n$, the user n has a predetermined daily energy demand e_i and an operating time preference $[\alpha_i, \beta_i]$, where $1 \leq \alpha_i \leq \beta_i \leq H$, for the appliance to operate. α_i is the earliest time at which appliance i can start its operation and β_i is the deadline by which the appliance i needs to finish its task. For example, a user can set the operation of a washing machine to start in the evening and finish before the next morning. The user's HEMS needs to schedule and fulfill the energy requirement of each flexible appliance to finish its task within the time preference, denoted as

$$e_i = \sum_{h=\alpha_i}^{\beta_i} x_{n,i}^h, \forall i \in \mathcal{A}_n, \tag{3.1}$$

where $x_{n,i}^h$ is an energy consumption of the flexible appliance i belong to the user n in hour h. Also, the energy consumption of appliance i has minimum and maximum bounds it can consume in each hour as

$$x_{n,i}^{h,min} \leq x_{n,i}^h \leq x_{n,i}^{h,max}. \tag{3.2}$$

The user also has a set of non-flexible appliances and the sum of its energy demand is defined as $x_{n,o}^h$, which is predetermined and cannot be altered. An example of the energy consumption pattern of appliances before and after scheduling is illustrated in Fig. 3.3. Finally, the energy demand for household appliances of user n is defined as

$$d_n \triangleq [d_n^1, d_n^2, ..., d_n^H] \tag{3.3}$$

where $d_n^h = x_n^h + x_{n,o}^h$ and $x_n^h = \sum_{i=1}^A x_{n,i}^h$ is the sum of all flexible appliance's consumption in hour h.

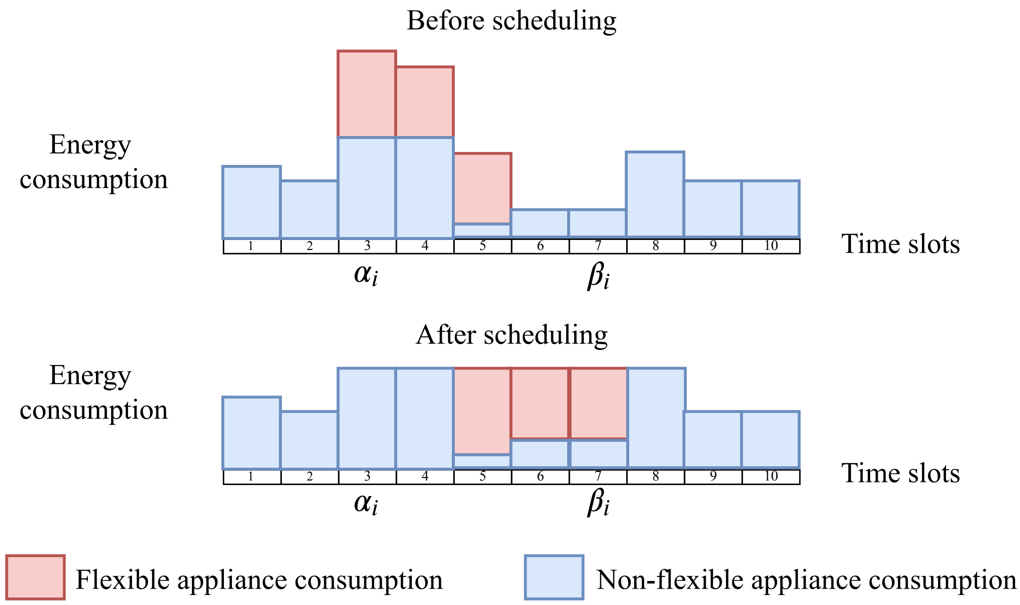

Figure 3.3: Example for the energy consumption pattern of appliances before and after scheduling.

3.2.2 Photovoltaics System

The users may be equipped with PV that can produce energy locally. A forecast daily PV generation at the user n's premises is denoted as

$$g_n \triangleq [g_n^1, g_n^2, ..., g_n^H]. \tag{3.4}$$

Since energy generated from PV has only fixed installation cost and implies no strategy regarding energy production, we assumed that PV generates electricity at its maximum available power and considered as a *passive DER*. We also assumed an accurate day-ahead PV generation forecast. We prioritize the user to directly consume energy from PV whenever it available. Then, if the energy is not sufficient to meet the demand, the user seeks energy from other available sources: battery storage, local energy sharing, or the main grid.

3.2.3 Battery Storage System

The users may also own PV with battery storage systems at their premises. The operation of the battery can be scheduled as an *active DER*, which is limited by its physical characteristics. We denote the battery capacity by Q_n and define y_n^h as the energy charging or discharging of user n for her battery at time slot h, where $y_n^h \geq 0$ indicates charging and $y_n^h < 0$ indicates discharging. Charging and discharging are subjected to battery efficiency rate η_c and η_d, respectively. Hence, the battery storage scheduling vector is defined as

$$y_n \triangleq [y_n^1, y_n^2, ..., y_n^H]. \tag{3.5}$$

The energy level stored in the battery at each time slot is indicated by state of charge (SOC) as

$$SOC_n^h = SOC_n^{(h-1)} + \frac{y_n^h}{Q_n}, \tag{3.6}$$

where $SOC_n^{(h-1)}$ is the SOC level in the previous time slot. An initial SOC_n^0 is predetermined and the final SOC (SOC_n^H) is assumed to be the same as SOC_n^0

$$SOC_n^H = SOC_n^0. \tag{3.7}$$

The SOC level is usually limited by maximum and minimum SOC ranges as

$$SOC_n^{min} \leq SOC_n^h \leq SOC_n^{max}, \ \forall h \in \mathcal{H}. \tag{3.8}$$

Furthermore, maximum charging/discharging rates in each hour are limited as

$$-y_n^{max} \le y_n^h \le y_n^{max}. \tag{3.9}$$

3.2.4 Net Energy Consumption

We define user n's net energy consumption in time slot h as

$$l_n^h = d_n^h - g_n^h + (\frac{1}{\eta_c})max(y_n^h, 0) + \eta_d min(y_n^h, 0). \tag{3.10}$$

and the corresponding consumption scheduling vector over H time slots as

$$l_n \triangleq [l_n^1, l_n^2, ..., l_n^H]. \tag{3.11}$$

Based on the net energy consumption, in each time slot, a user's role is classified as *a buyer* or *a seller*:

- A buyer: When $l_n^h > 0$, the user needs to purchase energy from the CEC to meet his demand
- A seller: When $l_n^h < 0$, the user has energy surplus to be sold to the CEC

Hence, we define the selling energy $e_{s,n}^h$ and buying energy $e_{b,n}^h$ of the user n in time slot h as

$$e_{s,n}^h = min(l_n^h, 0) \tag{3.12}$$

and

$$e_{b,n}^h = max(l_n^h, 0), \tag{3.13}$$

respectively. As the net energy consumption is expressed as a sum of different device demand and generation, including flexible and non-flexible parts, the user has the flexibility to shift his consumption by the scheduling of flexible appliances $x_{n,i}^h$, $\forall i \in \mathcal{A}_n$ and charging/discharging of a battery y_n^h in each time slot h for all considered scheduling horizon

$\mathcal{H}$.

3.3 Demand-Side Management Model

In this section, we explain the detail of price-based DR and local energy sharing in the proposed DSM model. A block diagram of the proposed DSM model is shown in Fig. 3.4. The utility company and CEC interact with each other via grid energy prices. The utility company determines the grid energy prices based on the aggregate consumption profile of the community. The CEC receives a grid price function from the utility company and incorporates into its local energy price functions. To incentivize local energy sharing, the CEC sets the local energy prices between grid buying and selling prices so that all prosumer receives an economic incentive from the local energy sharing at all times. Then, when user's HEMS receives local energy prices (selling and buying prices) from the CEC, it schedules energy consumption of appliances and battery in order to maximize economic benefits, e.g., bill savings. Since local energy prices depend on not only local supply and demand but also a dynamic of grid prices, all user's HEMSs need to coordinate consumption scheduling which resulting in a reduction of peak demand and export energy. Thus, the dynamic energy prices (more detail in Chapter 4) can be viewed as a method to indirectly control the community consumption behavior to align with the utility company's desire consumption profiles. The details of the utility company and the CEC models are described next.

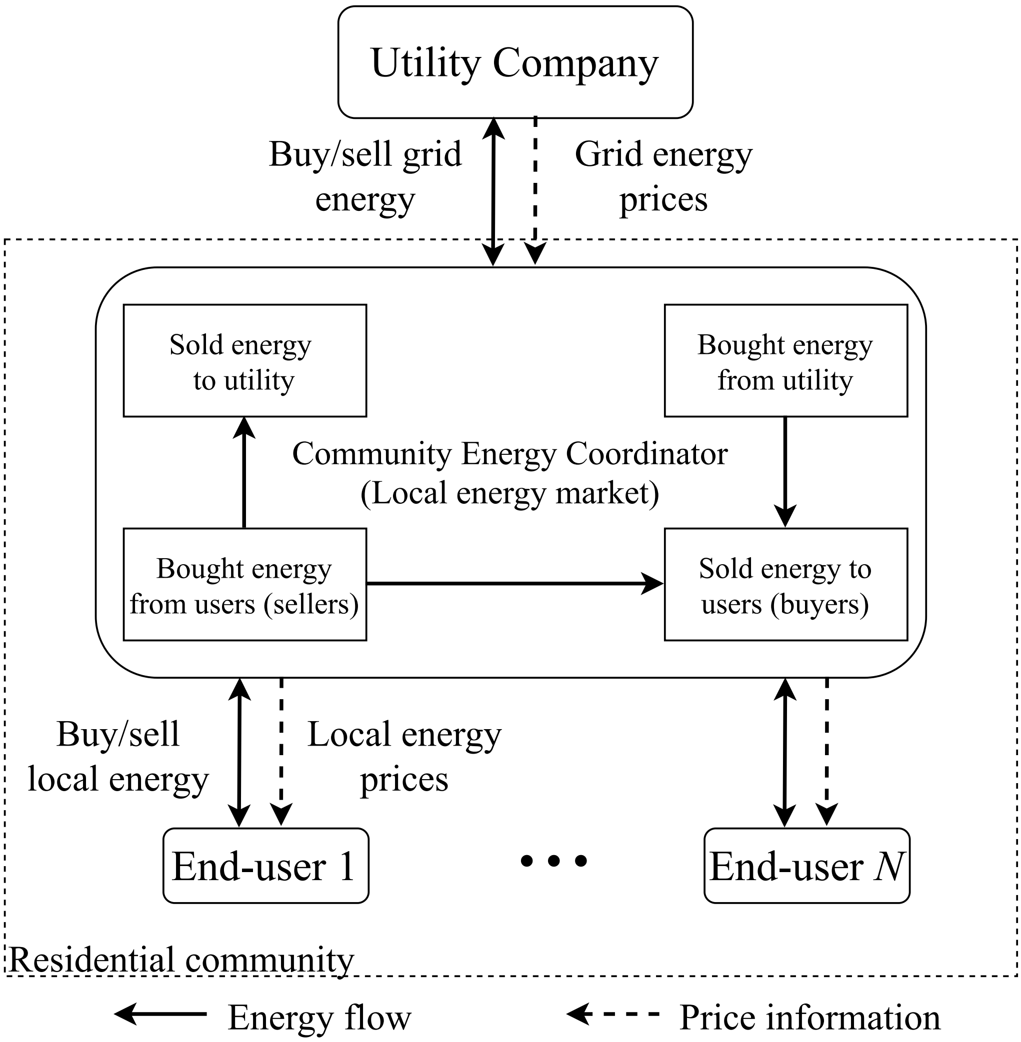

Figure 3.4: A block diagram of the proposed DSM model with the community energy coordinator in a residential community.

3.3.1 Utility Company Model

The utility company is responsible for providing energy to the community or purchasing any excess energy from the community as in the FIT program [80]. Even though wholesale prices can fluctuate rapidly by significant amounts, most of the current utility companies hide complexity and volatility from their customers and offer a fixed unit electricity price (flat-rate tariff) or multiple tiers based on a customer's consumption. Usually, the wholesale prices are determined by demand and supply and by congestion in the transmission network, whereas, the retail prices are set statically independent of the real-time load and congestion. The flat-rate pricing has the advantage of being predictable and straightforward, but it does not encourage the efficient use of electricity.

To encourage efficient use of electricity, price-based DR schemes have been proposed in recent literature. The utility company could use a dynamic pricing scheme in the retail market, where the price of energy depends on the aggregate community consumption. The design of the retail price needs to at least recover the running costs of the utility company, including the payments it incurs in the wholesale market. Many works in the DR literature [8, 30, 37, 41, 81] commonly summarized the energy cost of the utility company into a cost function $C(L, h)$ which specifies the cost for providing L amount of energy to the users at any given time h. The energy price $p(C(L, h))$ can be set by the utility company as a function of the energy cost and announce to the users. The price function is used as a tool for encouraging users to follow the desired energy consumption pattern of the utility company. Thus, the utility company can coordinate the users' demand responses to the benefit of the overall system as well as individual users in the community.

3.3.2 Community Energy Coordinator Model

With a traditional FIT scheme, users in the community usually manage PV and battery systems from an individual user's perspective by maximizing the self-consumption of the customer's generation. If there is insufficient energy from the private generation, the users purchase deficit energy from the utility company, and when there is excess energy, the surplus is sold back to the utility company. However, due to the significant lack of equality and similarity between the buying and selling prices per unit of energy, the economic benefit to users for participating in energy trading with the utility company is not significant enough. With the little economic gain, the users may face difficulty to payoff their DER investment and discourage the new customers from investing in DERs. As a result, it is important to create new energy markets that allow users with small-scale DERs to actively trade energy locally with each other and facilitate a sustainable and reliable balance between the generation and consumption of energy within the community

[82].

Local energy trading is being considered as a potential tool to promote the use of DERs within the community. To facilitate the local energy sharing organization, the CEC is introduced as the interface between the utility company and users inside the community. We define the roles and responsibilities of the CEC in the community as follows.

- It ensures the energy balance of the community, by act as an agent to trade energy with the utility company on behalf of users in the whole community.
- It manages local energy sharing between buyers and sellers by collects the energy demand request and/or energy offer from the users and resolve energy discrepancies by buying energy from, or selling excess energy back to the grid whenever necessary.
- It specifies the market rules for local trading which include local energy pricing model, metering, billing mechanisms, and implementation process.

3.3.3 Demand-Side Management Procedure

In our proposed DSM model, we divide the DSM procedure into three sequential processes shown in Fig 3.5: day-ahead consumption scheduling (Chapter 4), consumption rescheduling (Chapter 5), and energy billing (Chapter 6). The detail of each procedure is described as follows.

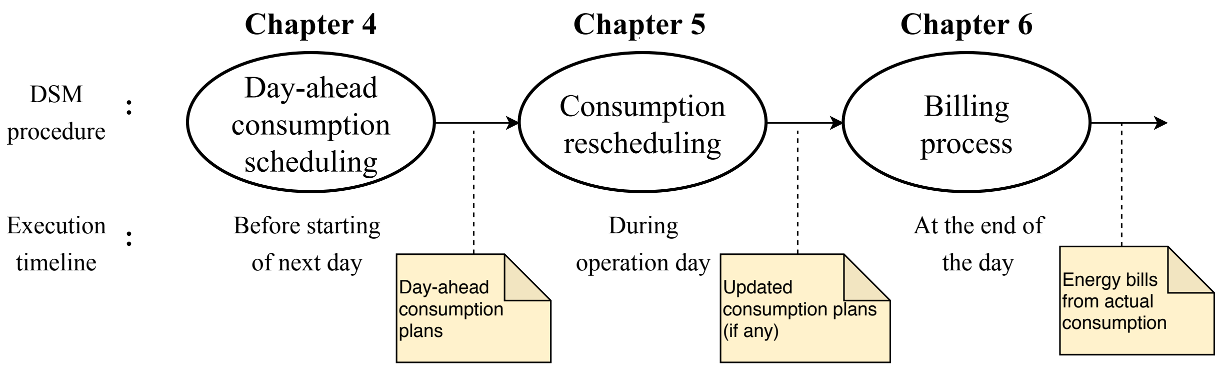

Figure 3.5: A flow diagram of the DSM procedure.

- Day-ahead consumption scheduling is executed at the end of each day to plan the energy consumption of each user in the following day. Each user assigns flexible appliances and a period the appliances can operate in HEMS. Also, the utility company provides the grid price functions (price coefficients) to the CEC. Consequently, the CEC incorporates the grid price function into its local price function and broadcast to all users at the beginning of the DSM process. Then, coordinated by the CEC, all users' HEMSs schedule day-ahead energy consumption of flexible appliances and battery operation based on given price functions to minimize individual daily energy bills. The resulting consumption schedules are sent back to the CEC. Then, the CEC aggregates the energy request and offers from the users and determines if it needs to import or export energy from the utility company. Finally, the CEC informs the utility company of the final day-ahead aggregate community consumption schedule.

- Consumption rescheduling process is executed during the operation period (during $h = [1, ..., H]$). Before the beginning of each hour, if there is any user who wants to change his preferences, he can request to the CEC for rescheduling of his consumption plan. The CEC coordinates the request from all users and provides updated community consumption information to the requested users. Then, the users' HEMSs recalculate the consumption schedule and battery operation for the remaining time slots and inform the updated schedule back to the CEC for future use.

- The Billing process is executed at the end of the operation period. The CEC calculates the energy bill of all users in the community based on their actual consumption. If any violation of the assigned schedule, the CEC allocates penalty or reward to the users based on their deviated consumption to maintain billing fairness in the community.

3.4 Chapter Summary

In this chapter, we explained the structure of the community energy system, which consists of the utility company and the residential community. The community is composed of residential users equipped with DER. We defined the role and responsibility of each entity in the considered energy system. Then, we explained the proposed DSM model and described the procedure. The detail of each DSM procedure will be presented in the following chapters. The publications related to this chapter can be found in the publication list [1] and [3].

Chapter 4

Day-ahead Consumption Scheduling

In this chapter, we propose energy pricing functions in the DSM model for day-ahead consumption scheduling in a residential community with a high penetration of DER. We introduce the CEC to facilitate energy sharing inside the community and a local energy market that incentivize all user to share energy while benefiting the utility company, creating a *win-win* scenario. Then, we formulate an energy bill minimization optimization problem for each user. An iterative distribution decision-making approach is used to find all users' optimal consumption schedules in the community. Simulation results are given to demonstrate the benefits of our proposed DSM model to the utility company and its users at the end of this chapter.

4.1 Price-based Demand Response with Local Energy Sharing Model

The goal of energy pricing design is to encourage users to change their consumption patterns such that it smoothes the aggregate community consumption profile, reduces peak demand and export energy, which in turn also reduces the total energy cost. The users' HEMSs use the energy price information to plan their consumption by shifting load, scheduling of battery operation, and sharing energy among users to reduce their energy bills. In this section, the detail grid energy pricing of the utility company and local energy pricing of the local energy market are described as follows.

4.1.1 Grid Energy Pricing Model

We design a grid energy pricing model for the utility company to charge for the energy demand of the community. In our model, the utility company provides energy service for the users through the CEC, who represents all the users inside the community.

Let $L^h = \sum_{n=1}^{N} l_n^h$ be the aggregate net energy consumption of the community at time slot h. A dynamic energy price (grid buying price) in hour h is determined by the utility, which is a linear function of the total energy demand of the community ($L^h \geq 0$), and defined as

$$p_{g,b}^h = a^h L^h + b^h, \tag{4.1}$$

where a^h and b^h are coefficients selected by the utility company. The grid buying price function is related to an energy cost that the utility company procures energy from generators in the wholesale market. Due to the fact that a marginal cost of producing energy is increasing as the amount of required energy increases, the energy cost is assumed to be a quadratic function of the total energy demand. Thus, the energy cost in time slot h is defined as

$$C^h = a^h (L^h)^2 + b^h L^h. \tag{4.2}$$

Note that the choice of the quadratic energy cost function that varies with the total energy demand is common assumptions in the literature [8, 30, 37, 41, 81], where the cost function is a general approximation of efficient markets and not tailored to a specific market. Fig 4.1 shows an example of energy cost and price as a function of energy. On the other hand, when there is a surplus of energy in the community ($L^h < 0$), the CEC sells the surplus back to the grid as in the FIT program. In this research, the grid selling prices $p_{g,s}^h, \forall h \in \mathcal{H}$ are assumed flat-rate tariffs. We also assumed that the utility company employs *a budget balanced* scheme, where the total revenue of the utility company is equal to its energy costs. The design of the linear price function will encourage users to shift their energy consumption from the peak-demand periods to off-peak periods to avoid high energy prices and thus flatten the demand profiles.

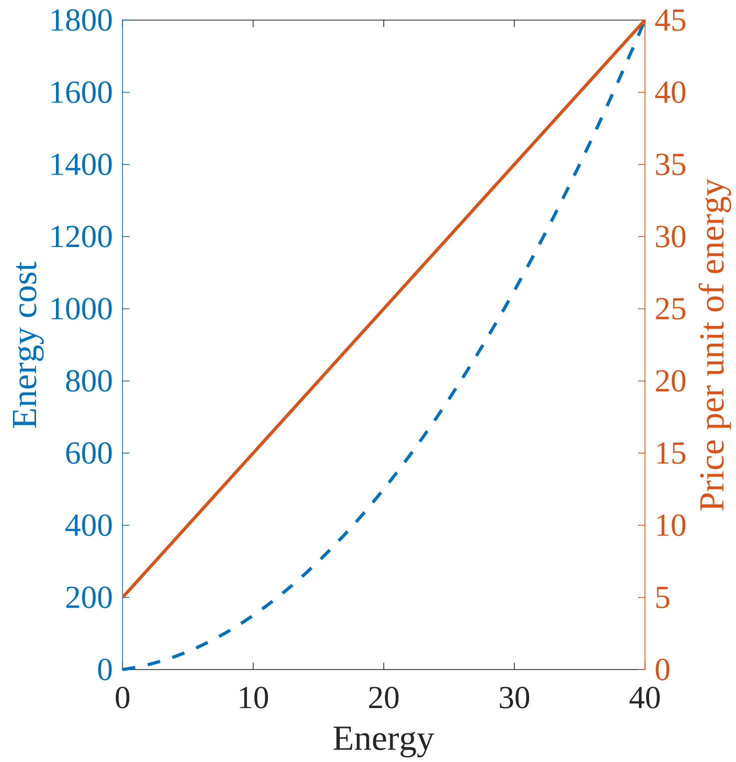

Figure 4.1: Example of grid energy cost and price as a function of energy.

4.1.2 Local Energy Pricing Model

For the local energy pricing model, we propose to incorporate the dynamic of the grid price into the local energy sharing market by defining energy prices inside the community to dynamically changed depending on local energy supply and demand as well as the defined grid energy prices. We apply the concept in economics and the relation between demand and supply [67] to formulate local energy price function. More specifically, the local energy pricing model is a function of the aggregate net energy consumption L^h, as well as the ratio of total local energy supply E_s^h and demand E_b^h. First, let define the total selling energy and total buying energy of the community in hour h as

$$E_s^h = \sum_{n=1}^{N} e_{s,n}^h \tag{4.3}$$

and

$$E_b^h = \sum_{n=1}^{N} e_{b,n}^h, \tag{4.4}$$

respectively. A supply and demand ratio (SDR) in hour h can be calculated as

$$SDR^h = \frac{\left|E_s^h\right|}{E_b^h}. \tag{4.5}$$

To incentivize local energy sharing at all time, the local selling price $p_{l,s}^h = f(p_{g,b}^h, SDR^h)$ should always greater than or equal to the price of energy sold to the utility company and the local buying price $p_{l,b}^h = f(p_{g,b}^h, SDR^h)$ should always lower or equal to the price of energy bought from the utility company. That is

$$p_{g,s}^h \leq p_{l,s}^h \leq p_{l,b}^h \leq p_{g,b}^h. \tag{4.6}$$

Based on inverse-proportional relationship between price and SDR, the local selling price function is defined as

$$p_{l,s}^h = \begin{cases} \frac{p_{g,s}^h p_{g,b}^h}{(p_{g,b}^h - p_{g,s}^h) SDR^h + p_{g,s}^h} & , 0 \leq SDR^h \leq 1 \\ p_{g,s}^h & , SDR^h > 1. \end{cases} \tag{4.7}$$

Assume that the CEC also employ *a budget balanced* scheme, e.g., total revenue is equal to total expense, the local buying price function can be formulated as

$$p_{l,b}^h = \begin{cases} p_{l,s}^h SDR^h + (1 - SDR^h) p_{g,b}^h & , 0 \leq SDR^h \leq 1 \\ p_{g,s}^h & , SDR^h > 1. \end{cases} \tag{4.8}$$

When $SDR^h = 0$ means that there is no seller in the community and the energy requested from the buyers is imported from the grid by the CEC. Thus, both local selling and buying prices of energy are set equal to the grid buying price $p_{g,b}^h$. On the other hand, when the community has a surplus of energy ($SDR^h > 1$), all local demand is fulfilled by local supply and community surplus is sold to the grid. Thus, both local selling and buying prices drop to the grid selling price $p_{g,s}^h$. The local selling and buying prices are different when $0 < SDR^h < 1$ and would dynamically change and bounded by the grid buying and selling prices. A detail of the local price function formulation is provided in Appendix A.

A relationship between the local energy prices and SDR is shown in Fig. 4.2.

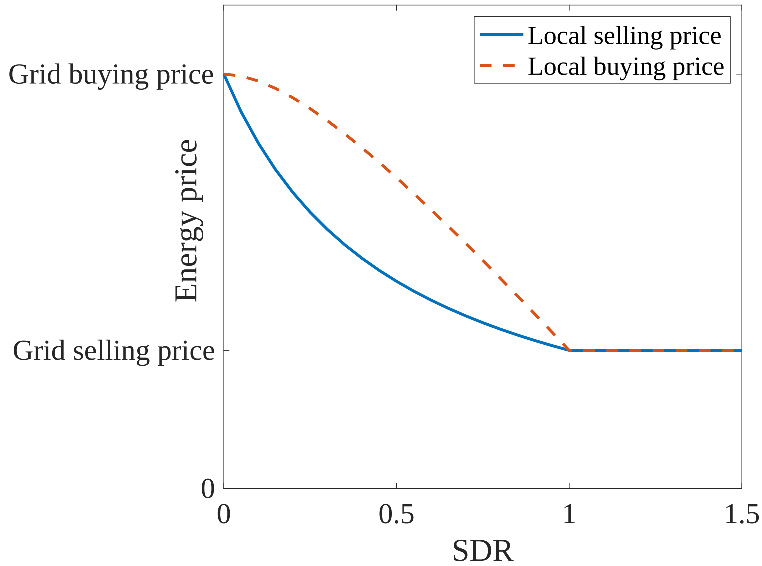

Figure 4.2: A relationship between local energy prices and SDR.

To explain the relationship between local energy pricing and the response of the users, we analyze as follows. With the increasing of SDR on the interval of [0, 1], the local selling price $p_{l,s}$ and buying price $p_{l,b}$ decline. Since we desire to maximize the usage of PV generation, the value of SDR is only be adjusted by the scheduling of the appliance's consumption and battery of users. In the user's viewpoint, which aiming to reduce his energy bill, when SDR is too small and the energy prices are too high, the buyers would want to lower their energy consumption in this period, and the sellers would also want to sell more energy for a high selling price. Thus, the SDR value would increase from decreasing demand. On the other hand, if SDR is too large and the energy prices are too low, the buyers would want to increase their energy consumption in this period, and the sellers would also want to increase the amount of self-consumption by shifting energy demand to this time since the selling price is low. Thus, the SDR value would decrease from increasing demand. Since we assume that the users have a certain portion of active

DERs, all users' HEMS can coordinate to manage their DER until the final SDR value has been agreed, which consequently affects the final local energy prices of the community. Furthermore, both local selling and buying prices also affected by the change of the grid buying price that depends on the net energy consumption of the whole community. This would emphasize the energy prices, especially during peak-demand periods. As a result, more demand would be shifted away from the peak time. Hence, the local energy market can effectively encourage the responses of users through the proposed price-based DR model.

4.2 Energy Bill Minimization Problem Formulation

In this section, we define a user's objective function and formulate an energy bill minimization problem for each user's HEMS to schedule energy consumption for the next H hours in the day-ahead consumption scheduling process. A user's energy bill is calculated from his energy consumption or production and the local energy prices in each time slot:

$$b_n^h = e_{b,n}^h p_{l,b}^h + e_{s,n}^h p_{l,s}^h. \tag{4.9}$$

Since the user can only be a buyer role or a seller role in each hour h, we rewrite (4.9) as

$$b_n^h = l_n^h p_l^h, \tag{4.10}$$

where $p_l^h = \begin{cases} p_{l,b}^h & , l_n^h \geq 0 \\ p_{l,s}^h & , l_n^h < 0 \end{cases}$. Each user is assumed to be *selfish* and has the objective of minimizing his own daily energy bill. Total daily energy bill of user n can be calculated as

$$B_n = \sum_{h=1}^{H} b_n^h. \tag{4.11}$$

We denote $\mathcal{Z}_n$ as a set of feasible energy consumption for the flexible appliances and battery operation of the user n respected to the constraints in (3.1), (3.2), (3.7), (3.8), and (3.9). The individual user n's optimization problem can be expressed as

$$
\begin{aligned}
\underset{\mathbf{z}_n \in \mathcal{Z}_n}{\text{minimize}} \quad & B_n(\mathbf{z}_n) \\
\text{subject to} \quad & e_i = \sum_{h=\alpha_i}^{\beta_i} x_{n,i}^h, \forall i \in \mathcal{A}_n \\
& x_{n,i}^{h,min} \leq x_{n,i}^h \leq x_{n,i}^{h,max}, \forall h \in \mathcal{H} \\
& y_n^{min} \leq y_n^h \leq y_n^{max}, \forall h \in \mathcal{H} \\
& SOC_n^{min} \leq SOC_n^h \leq SOC_n^{max}, \forall h \in \mathcal{H} \\
& SOC_n^H = SOC_n^0
\end{aligned}
\tag{4.12}
$$

where $\mathbf{z}_n \triangleq [x_n^1, x_n^2, ..., x_n^H, y_n^1, y_n^2, ..., y_n^H]$ is a decision vector containing energy consumption of the appliances and battery operation over the scheduling period H.

4.3 Iterative Distributed Decision-Making Approach

The optimization problem formulated in the previous section could be solved in a centralized fashion, with the central unit imposing every user how much energy he must consume, produce, charge, and discharge at each hour. However, this approach is quite an invasion solution since it requires each user to provide detailed information about his preference and demand for each appliance, energy production, and battery storage capabilities. Such a privacy issue may discourage users from participating in the DSM. Moreover, a centralized approach cannot account for an unpredictably expanding number of participants and not scalable. In consequence, we instead interest in a distributed solution and apply an iterative decision-making approach that preserves the privacy of individual users regarding their consumption details.

Let rewrite the aggregate net energy consumption as

$$L^h = l_n^h + L_{-n}^h \tag{4.13}$$

where $L_{-n}^h = \sum_{m=1, m\neq n}^{N} l_m^h$ is the sum of all users' net energy consumption except user n.

Furthermore, (4.3) can be rewritten as

$$E_s^h = e_{s,n}^h + E_{s,-n}^h \tag{4.14}$$

where $E_{s,-n}^h = \sum_{m=1,m\neq n}^{N} e_{s,m}^h$ is the sum of all users' selling energy surplus except user n. Similarly, (4.4) can be rewritten as

$$E_b^h = e_{b,n}^h + E_{b,-n}^h \tag{4.15}$$

where $E_{b,-n}^h = \sum_{m=1,m\neq n}^{N} e_{b,m}^h$ is the sum of all users' buying energy demand except user n. Now, the HEMS of user n can individually solve the problem (4.12) with only local variables as long as she has the information of the grid price function, local pricing functions, aggregate net energy consumption $L \triangleq [L^1, ..., L^H]$, total buying energy $E_b \triangleq [E_b^1, ..., E_b^H]$, and total selling energy $E_s \triangleq [E_s^1, ..., E_s^H]$ of the community. The information necessary for solving the optimization problem is provided by the CEC as public information and does not reveal any private information of the user.

The overall process is implemented in a closed-loop iterative fashion. The summary of the consumption scheduling procedure for each user is presented in Algorithm 1. Initially, a HEMS of each user $n \in \mathcal{N}$ randomly initializes consumption vector $\mathbf{z}_n$ since no prior information about the community energy consumption is known. The CEC selects a user, in random order, to schedule energy consumption and sends the current community consumption information (L, E_s and E_b) and local energy price functions to the selected user's HEMS. Then, the HEMS solves the optimization problem to minimize daily energy bill according to (4.12). If the consumption schedule solutions different from the previous solution, the HEMS updates the community parameters L, E_s and E_b by substituting the previous solutions with the new one and announces them back to the CEC. The CEC selects the next user and repeats the process until no user changes her schedule and the algorithm is terminated. Otherwise, when the algorithm reaches predetermine maximum iterations, it terminates with the solutions in the last iteration. Finally, the CEC collects final consumption schedules from all users' HEMSs. Note that users do not need to reveal the details of their preferences and appliance specification, only total energy consumption is sent to the CEC and not reveal to other users, which protect the privacy of the users. A flow chart of the algorithm is shown in Fig. 4.3.

Algorithm 1 Consumption scheduling: executed by HEMS of each user $n \in \mathcal{N}$

Input: L, E_s and E_b
Output: Consumption schedule $\mathbf{z}_n^*$
choose any feasible starting point $\mathbf{z}_n^0 \in \mathcal{Z}$
repeat
  when receive execute command and L, E_s, E_b from the CEC
   solve local optimization problem (4.12) for $\mathbf{z}_n$
   if $\mathbf{z}_n$ *changes compare to the previous consumption schedule* ($\|\mathbf{z}_n - \mathbf{z}_{n,prev}\| \geq \epsilon$) **then**
    update L, E_s and E_b with the new $\mathbf{z}_n$
    announce L, E_s and E_b to CEC
  end
until *no consumption schedule is updated or reach maximum iteration threshold*

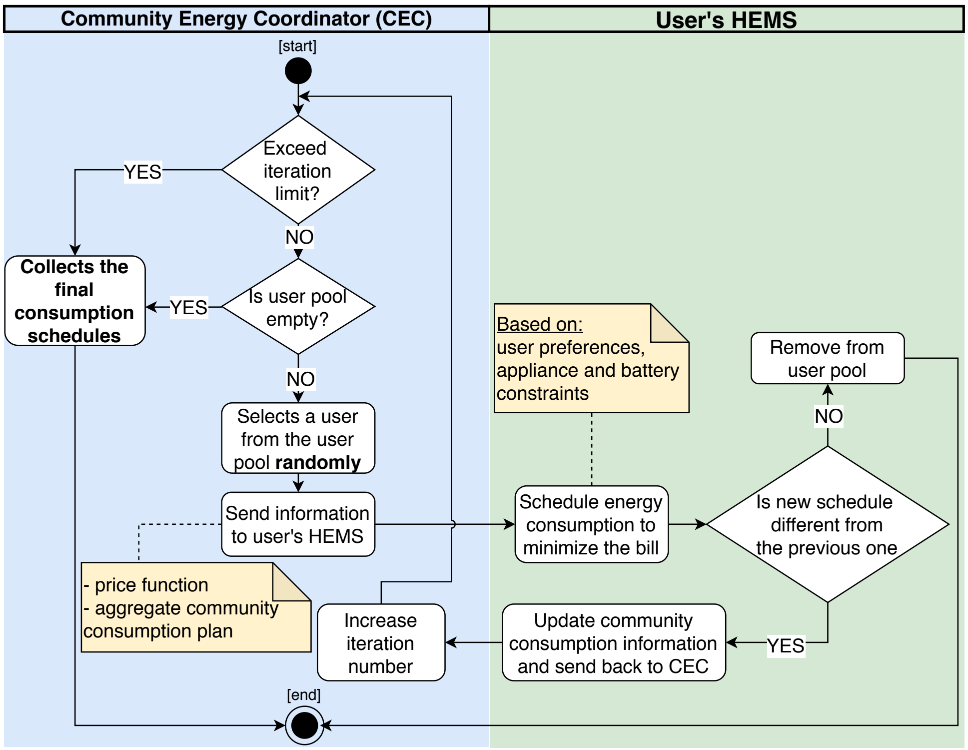

Figure 4.3: Flow chart of the iterative distributed decision-making algorithm

4.4 Simulation Results

In this section, we define system performance metrics and conduct numerical simulations to demonstrate the ability to reduce the energy bill of the community while flattening the grid demand profile of our proposed DSM system. We further compare our model with other models based on price feature differences and analyze the value of each feature on the system performances. Furthermore, several study cases are provided to evaluate the impact of battery, PV generation, and user participation in the proposed system.

4.4.1 System Performance Metrics

We define assessment metrics to quantify the performance of the proposed DSM model as follows:

Total Community Energy Bill

The energy bill of the community is calculated from the sum of all users' energy bills. This is also the payment of the CEC to the utility company as it trades energy on behalf of the whole community.

Total Energy Export and Self-consumption Rate

The surplus of PV generation is exported back to the grid if it exceeds the demand of the whole community. The total energy export is calculated as the sum of energy inject to the grid in each hour. A large injected energy could cause issues to the existing equipment and practices used to manage the local distribution networks. A self-consumption rate is defined as the ratio between the PV generation utilized locally within the community and the aggregate PV generation from all users. It measures how much local generation has been consumed on site. In other words, it focuses on where the local generation goes.

Total Energy Import and Self-sufficiency Rate

The energy demand of each user can be supplied from local or external energy sources: local PV generation, local battery storage, local energy sharing, and grid import. The total energy import is defined as the energy required to fulfill the community demand from the grid. A self-sufficiency rate is defined as the ratio between the energy demand that is fulfilled by the local generation and the total energy demand of the community. It measures how much users' demand can be supplied by local generation, including local energy sharing within the community. That is, it reflects the energy dependency of the community on external sources.

Peak Demand and Peak-to-average Ratio

The utility company interests in the aggregate consumption profile of the community as it needs to procure the energy from generators or the wholesale market to meet the demand. Peak demand is one of the critical concerns that the utility company uses to determine economic dispatch. The peak demand is defined as the maximum value of the aggregate energy consumption profile of the community. Furthermore, a peak-to-average ratio (PAR) is defined as the ratio of peak load and average load over a period of time (24 hours in this case). It measures the flatness of the consumption profiles and reflects the maximum dispersion of the demand from the average. The utility company favors low peak demand and PAR as it can eliminate the need for more expensive generation sources and, thus, lower the energy costs and prices.

4.4.2 Simulation Setting

We performed simulations based on a residential community with $N = 100$ users equipped with a PV system. We assume that 30% of the population also owns an additional battery storage system [1]. The consumption scheduling process is done for the next $H = 24$ hours. A lithium-ion battery specification is based on a small-scale household battery from sonnenBatterie eco 8.0 [83] with a capacity of 6 kWh. The battery has a one-way efficiency of 98% and an inverter efficiency of 96%. The SOC_n^{min} and SOC_n^{max} is set to 0.08 and 0.88, respectively. The maximum charging/discharging rates are 3 kW. The initial SOC of 0.5 is assumed for all users at the beginning of the scheduling period.

The coefficients of the energy generation cost function are assumed to be $a^h = 0.47$ and $b^h = 18.62, \forall h \in \mathcal{H}$ and are determined by line fitting of a modified tiered pricing structure of the TEPCO electric power company [84]. Note that, in practice, the selection of price coefficients could be different by each utility company and can be computed from real data used in the energy dispatch problem of the utility company or designed artificially such that the energy consumption of users can be manipulated according to the system desired outcome. Without loss of generality, we select the price coefficients as to demonstrate the impact of the proposed energy pricing functions on user's consumption behavior and the aggregate community consumption profiles. For the grid selling price $p_{g,s}^h$, we set as 14 JPY/kWh.

For appliance energy constraints, we assume $x_{n,i}^{h,min} = 0$ and $x_{n,i}^{h,max}$ equal to the maximum value observed in the generated consumption profiles. The type of appliance (flexible or non-flexible) is assigned to each appliance based on the importance of the appliance being used. For example, a refrigerator is needed to be on all the time and is classified as a non-flexible appliance. While a washing machine can be seen as a flexible appliance since a user can prepare clothes to be washed in advance and only concern for the time it finishes washing. Some of the appliances may be difficult to classify due to differences in the lifestyle of users. Also, each user specifies the preference for using his flexible appliances. We randomly assigned the preference for each user based on the generated appliance consumption profile such that the start and end time of the appliance can be shifted from the original value within two hours. For the iterative distributed algorithm, we set $\epsilon = 0.01$ and maximum iteration number of 500.

MATLAB software is chosen for the implementation of the DSM model, including the modeling of the appliances, battery, energy pricing mechanism, and consumption scheduling of HEMS. The optimization problem (4.12) of each user's HEMS is solved using MATLAB constrained nonlinear optimization toolbox. Note that, in this work, we focus on the effect of the proposed energy pricing schemes on the user's response behavior in the DSM context. The physical constraints of the electrical network are omitted in the model. To simulate more detailed simulation related to network parameters, other smart grid simulation tools, e.g., Gridlab-D [85], can be integrated, where the control function and decision-making on energy consumption are provided from MATLAB implementation in future work.

Domestic electricity generation tool

To generate appliance demand profiles for each user (house), we use a domestic electricity demand generation tool developed by the Centre for Renewable Energy Systems Technology (CREST) [3], which is also widely used in related research community [71, 74, 86–88]. A simplified structure of the CREST model is shown in Fig. 4.4. A summary of the tool is presented as follows: The CREST tool is capable of generating a synthetic daily electricity demand data of each installed appliance in the home, using an active occupancy data and daily activity profiles. The active occupancy data (indicates when people are at home and awake) is generated from an occupancy model, which uses a first-order time-inhomogeneous Markov-chain technique based on a time-use survey. The daily activity profile, also derived from the time-use survey, is representing the probability of the specified activity being undertaken, e.g., "cooking," as a function of time during a day, the number of active occupants, and whether it is a weekday or weekend. For each simulated house, a set of appliances and associated annual demand in kWh/year is assigned randomly based on a statistical ownership data. Thus, each house may have a different number of appliances. The total number of appliances in the selected pool is 31. The full list of appliances used in the simulation can be found in Appendix B. Each appliance is assigned to one of the daily activity profiles. There may be multiple appliances assigned to a single activity. For example, oven and microwave are all assigned to the cooking activity.

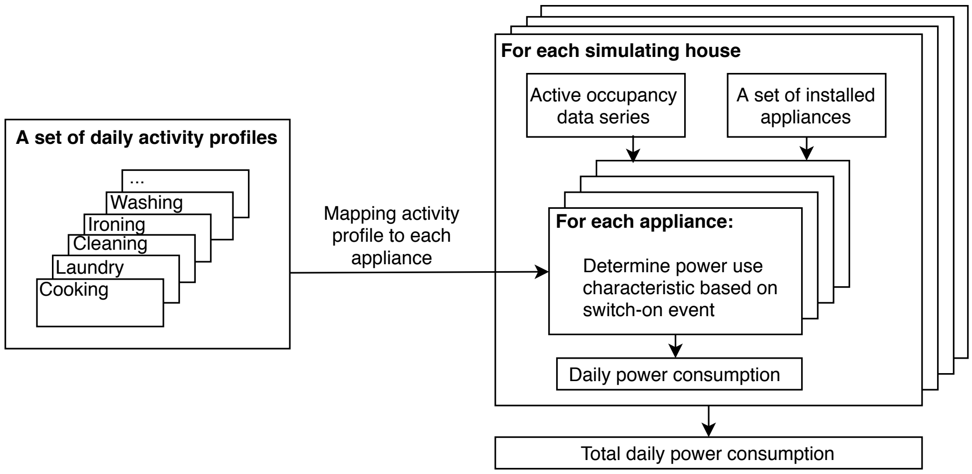

Figure 4.4: Simplified CREST demand generation model [3].

The CREST tool generates appliance consumption data by determining whether the appliance is switched on at each time step of a simulation. For each appliance, a procedure to determine the switch-on event is as follows: First, the activity profile associated with the appliance is selected. Second, the corresponding probability of any active occupants are engaged in the activity is read from the activity profile. Third, the probability is multiplied by the calibration scalar (which is the value to adjust the switch-on probability of the appliance such that the mean annual consumption of the appliance is agreed with the referenced statistical data) to get the probability of appliance switch-on at each time step. Finally, a random number between zero and one is generated and compared to the switch-on probability. If the probability is larger, the appliance is switched on, and power consumption is calculated. The process is repeated for each appliance in each time step until the end of the day. All of the generated consumption profile is then converted into a one-hour time step energy consumption.

The CREST model also provides a PV module to simulate PV generation using incident irradiance, PV panel array size, and system efficiency as input parameters. The incident irradiance is subjected to a panel orientation and surface area of the PV panel array. The solar irradiance profile is generated using a combination of clear sky irradiance and sky clearness index. The sky clearness index is representing the additional attenuation of the solar irradiance (due to weather condition) as compared to clear sky condition, which is constructed using the first-order Markov-chain technique based on the measured irradiance data set. We use a solar panel area of 10 m^2 with a system efficiency of 0.15 for all users. Due to a relatively small community area, all user's PV systems were considered to have the same generation profile.

The CREST model is validated with real-world measured data collected from 22 volunteer dwellings in UK. High-resolution meters were installed at each dwelling to collect the whole-house demand consumption, where 1-min intervals demand consumption were recorded throughout the year 2008. The measured data is then compared with the synthetic profile, generated from the CREST model. Similar characteristics were observed from both profiles which exhibit low electricity usage during late night and early morning periods, an increased usage throughout the day-time with similar spikiness. The individual dwelling's mean annual electricity demand of the synthetic and measured data sets is verified with only 1.2% deviation. Using a Mann-Whitney U-test with 5% level of significance, no significant statistical difference between the synthetic and measured data sets of annual and daily electricity demand between dwellings. Some discrepancies were observed in the daily demand profiles between two data sets. This is because of other factors that were not considered in the CREST model which affect the real-world electricity usage behavior such as employment profiles, energy conservation attitude, multi-tasking, and socio-economic factors. However, when comparing the synthetic data with national measured data, the CREST model is matched more closely than the actual measured data. Thus, the model is considered well represent of the overall domestic electricity demand rather than a specific small set of measured data.

The CREST electricity demand model is suitable for generating individual house consumption profiles for simulating the response of users in our DSM model. The availability of each appliance consumption profile in each house can be used for modeling user preference and flexibility of consumption schedules. Also, the CREST model can be configured for generating different types of houses and human activities associated with each appliance which can represent variation in the practice.

4.4.3 Case Scenarios

As of the current electricity structure, consumers are at the end of the electricity supply chain in a still predominant top-down structure: Generators sell their energy to retailers who offer electricity at flat-rate tariff electricity prices to the end-users. The price-based demand response program, with the installation of smart meters and HEMS, will open the possibility for end-users to see dynamic prices instead of a flat tariff in the near future.

To identify the value of each of the proposed DSM local market features: dynamic of grid condition and local energy supply and demand, three further case scenarios are compared: We add dynamic grid pricing and local energy sharing possibilities one by one to investigate its value to the system. We assume that exporting energy from the community to the grid is possible in all cases (users either directly export energy to the utility company or through the CEC). We summarized the case scenarios in Table 4.1 and detailed as follows:

- The **P2G+OTS** case is defined as a *base case* for the current's electricity structure. The users are only allowed to trade energy directly with the utility company, as in peer-to-grid (P2G) FIT scheme [6]. No energy price information is provided to the users, and the implementation of DSM is disabled. Thus, the users have no incentive to schedule their flexible appliance consumption, and the original consumption value is taken from the dataset. Battery operation of the individual house is applied "*Off-the-Shelf* (OTS)" control strategy [7,89], where the battery is charged based on the surplus of PV generation and discharged when local demand is higher than a local generation. Based on the above assumption, if the battery is not full, the battery charges as soon as the net consumption is negative. If the battery is not reached the minimum SOC level, it will discharges when the net consumption is positive. The OTS control strategy also constrained by the charge/discharge power limit of the system.

- The **P2G+DGP** case enables the DSM program where the grid energy prices depend on aggregate community consumption. The users still directly trade with the

Table 4.1: Feature summary of case scenarios

Case scenario	Appliance scheduling	Battery scheduling	Dynamic grid price	Local energy sharing
P2G + OTS	✗	✓ (OTS)	✗	✗
P2G + DGP	✓	✓	✓	✗
LES	✓	✓	✗	✓
LES + DGP	✓	✓	✓	✓

utility company as in the P2G FIT scheme and schedule their flexible appliance consumption and the operation of the battery based on the dynamic grid price (DGP) information. These assumptions are similar to the existing schemes in the literature, e.g., in [37, 39, 41].

- The **LES** case implements the local energy sharing (LES) mechanism inside the community through the CEC. The users in the community trade energy through the CEC and receive local energy price information from the CEC to schedule their flexible appliance and the operation of the battery. However, opposed to the P2G + DGP case, the dynamic of the grid price is not given to the users. These assumptions are similar to the existing schemes in the literature, e.g., in [67, 71, 74].

- The **LES+DGP** case is our *proposed* DSM model, where it offers both dynamic of the grid price and local energy sharing incentives in the energy price functions. The users trade energy with the utility company through the CEC, which determines local energy prices based on the SDR and DGP. The users' HEMSs use the local price information to determine consumption schedule of flexible appliances and the operation schedule of a battery.

4.4.4 Energy Consumption Profiles

First, we compare and analyze the energy profiles of the *P2G+OTS* (without DSM) case and our proposed *LES+DGP* (with DSM) case. Fig. 4.5 shows the energy profiles of the *P2G+OTS*. We can observe that the battery under the OTS algorithm discharged energy to supply the demand during morning and evening periods when there is no PV generation.

During mid-day, where PV generation is high, the battery charged the PV surplus until fully charged. However, since local energy sharing is not implemented, once the battery is fully charged, the exceed PV generation is export to the grid. Thus, creating a deep valley of the net energy profile. Furthermore, the battery can only suppress the peak demand until it reaches the minimum SOC level, and peak demand cannot be further reduced. Note that there is no shifting of flexible appliance consumption in this case, and thus, the reduction of export energy and peak demand are made solely by the battery. On the other hand, the energy profile in the *LES+DGP* cases is shown in Fig. 4.6. As a result of shifting flexible appliance consumption, the shape of the total demand is aligned with the PV generation. Then, together with the battery, the PV surplus, after fulfilling the local demand, is charged to the battery, resulting in zero export energy to the grid. The battery behavior is similar to the *P2G+OTS* case in timing but different in magnitude, where it discharged during morning and evening periods to supply the demand and charged during mid-day to absorb the PV surplus. Since some of the demand for flexible appliances can be shifted from the peak period, the battery can supply energy to the fixed appliance demand and thus able to further reduce the peak consumption than in the *P2G+OTS* case.

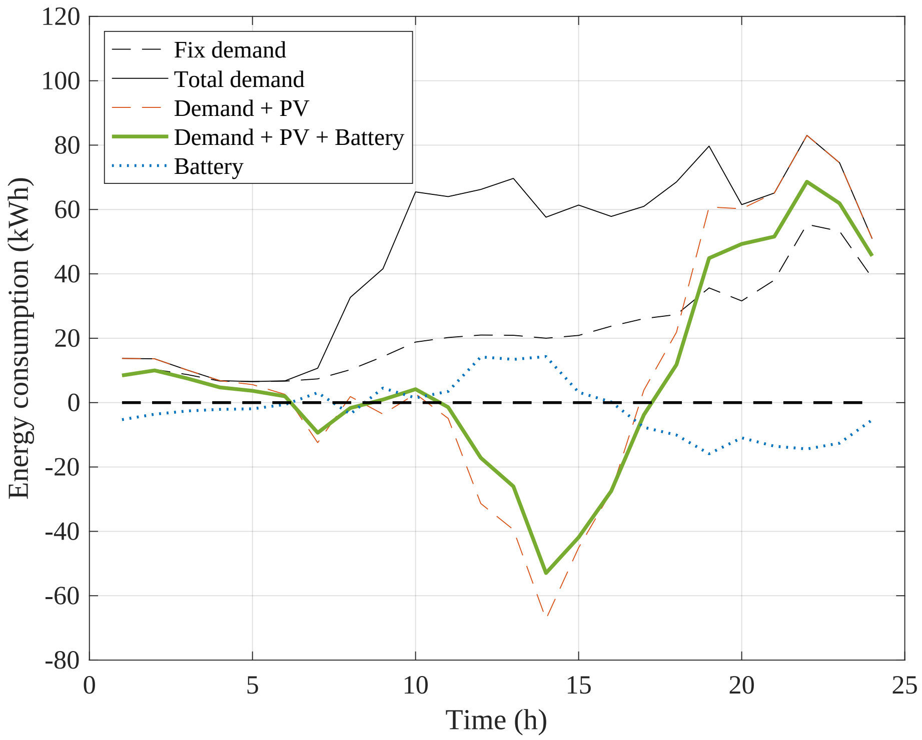

Figure 4.5: Aggregate energy profiles of P2G + OTS case scenario (base case)

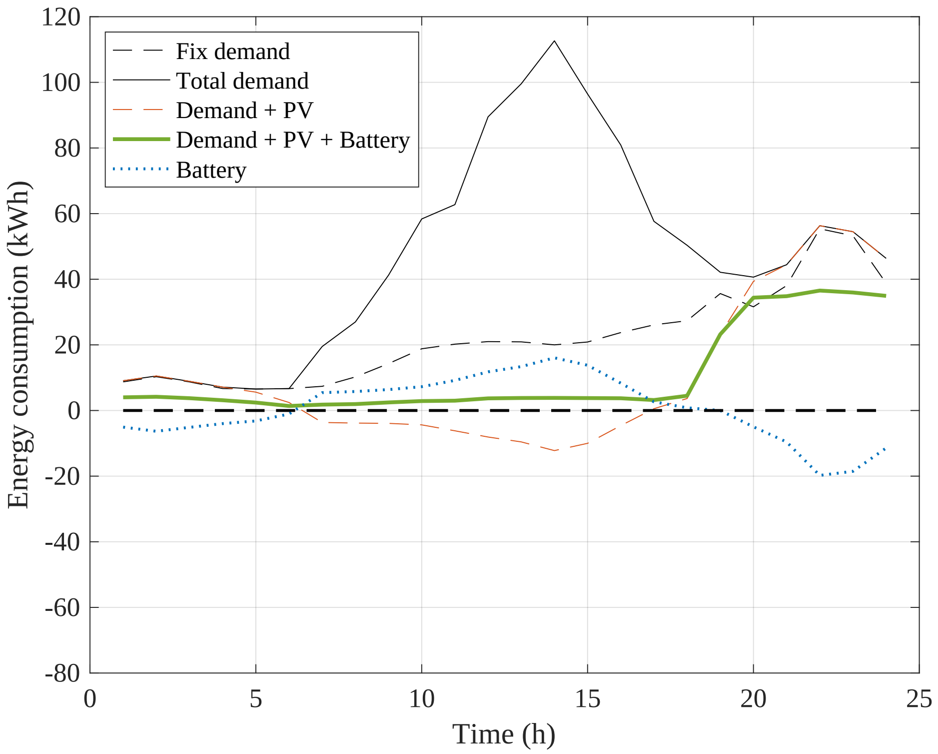

Figure 4.6: Aggregate energy profiles of LES + DGP case scenario (proposed)

4.4.5 Case Scenario Comparison

To compare the influence of dynamic grid pricing and local energy sharing features, the aggregate net energy consumption of the community in different cases is illustrated in Fig. 4.7. We observe a decrease in peak demand compare to the base case (*P2G+OTS*) when appliance consumption and battery scheduling is applied. In the proposed case (*LES+DGP*), when using a combination of dynamic grid pricing and local energy sharing features in the price functions, minimum peak demand is achieved. This is because the users react to the prices which reflect both the dynamic of the local supply and demand in SDR and also the dynamic of grid prices that depend on the total community energy consumption. The dynamic grid price feature, which only considered in the *P2G+DGP* case, performs better in terms of peak demand reduction than the *LES* case since the total community consumption is reflected in the price functions. However, since the users aim for minimizing individual energy bills without considering local supply and demand, the users' HEMSs tend to schedule energy consumption such that they can receive some profit from selling the excess energy back the grid. This is resulting in higher export energy compare to the cases that local energy sharing is enabled. On the other hand, in the *LES* case where only the dynamic of local supply and demand is presented in the price functions, the community export energy is eliminated and instead utilized inside the community via local energy sharing mechanism. The incentives provided by the local energy sharing motivate the users' HEMSs to schedule energy consumption such that the PV generation is locally consumed within the community.

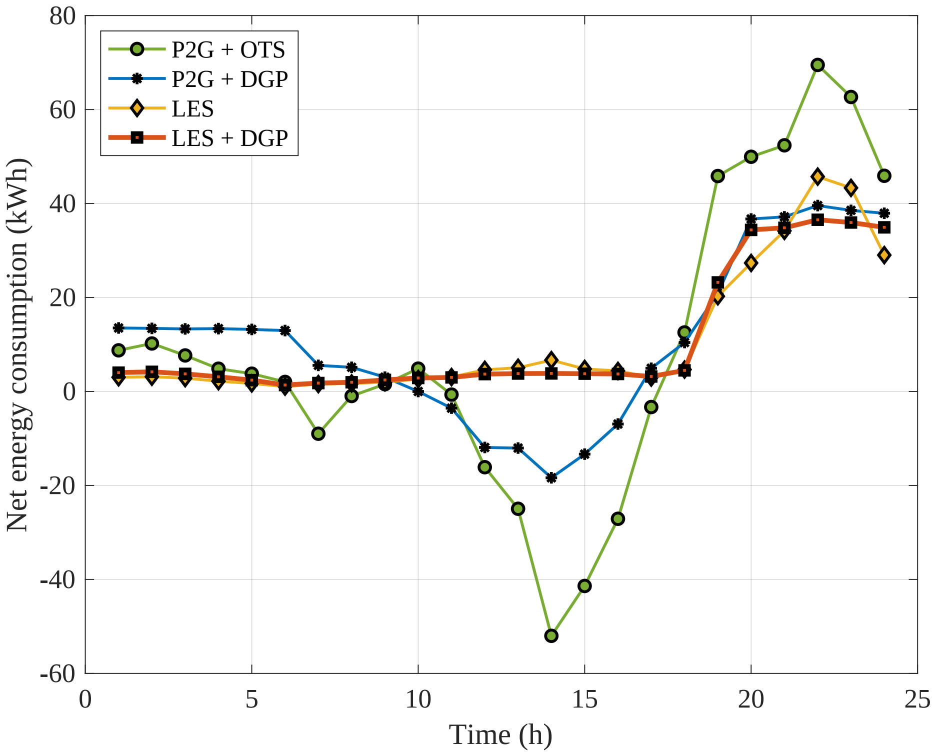

Figure 4.7: Net energy consumption of P2G + OTS (base case), P2G + DGP, LES and LES + DGP (proposed) case scenarios

The system performance of different case scenarios is summarized in Table 4.2. In terms of total energy bill reduction, the proposed *LES+DGP* case entails the highest monetary saving of the community with 43% bill reduction compared to the base case and 19.5% compared to the *P2G+DGP*. This confirm the benefit to the users in the community for participating in the proposed DSM. On the other hand, the influence of dynamic grid price in the *P2G+DGP* and *LES+DGP* cases can be found in peak demand and PAR reduction. The proposed *LES+DGP* case reduced PAR by 57.7% compared to the base case and 20% compared to *LES* case. This confirm the benefit to the utility company for flattening the demand curve of the community. Furthermore, the implementation of local energy sharing in the *LES* and *LES+DGP* cases show better improvement in export and import energy reduction leading to higher self-consumption (100%) and self-sufficiency (77.44%).

In short, the proposed *LES+DGP* case gain benefits from combining both the dynamic of grid price and local supply and demand into the price functions thus outperforms the cases when only one of the feature is applied. Therefore, we can conclude that the proposed energy price function could significantly reduce the total energy bill and efficiently reduce the peak demand and PAR in the aggregate load while improving the self-consumption and self-sufficiency of the whole community, achieving the *"win-win"* strategies for both the utility company and its customers. To sum up, the insights are highlighted as follows:

- The introduction of DSM with dynamic grid price with local energy sharing features leads to a total bill saving of 43%.
- The dynamic of the grid price implemented in the price function leads to a considerable reduction in peak demand and PAR.
- The local energy sharing incentive pricing leads to better improvement in self-consumption and self-sufficiency rates by the reduction in export and import energy.
- The combination of pricing features shows more considerable system improvement than implementing one of each feature separately.

Table 4.2: Comparison performance of difference case scenarios

Case scenario	Total community energy bill (Yen)	Self-consumption rate (%)	Self-sufficiency rate (%)	Peak demand (kWh)	PAR	Total export energy (kWh)	Total import energy (kWh)
P2G + OTS	14256	63.31	64.47	69.49	8.05	175.46	382.58
P2G + DGP	10029	75.61	71.88	39.56	3.74	66.11	319.74
LES	8263.2	100	77.39	45.72	4.25	0	257.99
LES + DGP	8072.2	100	77.44	36.54	3.40	0	257.36

4.4.6 Analysis of the Proposed *LES+DGP* Case

In this section, we analyze the characteristic of the proposed *LES+DGP* case. Fig. 4.8 shows the aggregate demand curve and the corresponding source of supply fulfilling the demand. We can observe that the grid import energy is exclusively necessary during evening peak hours. While most of the day, the majority of the demand can be fulfilled within the community by shifting flexible appliance consumption to meet with the peak PV generation and leveraging the local energy sharing from the surplus of PV generation to the individual user's demand. Batteries play a major role in supplying energy in the peak periods when PV generation is unavailable. Details of the battery's behavior can be seen from the SOC level shown in Fig. 4.9. The batteries tend to discharge at the beginning of the day to meet the morning demand. Then, starting to charge as the PV generation become available until reach the maximum SOC limit in the late afternoon. To meet the peak demand in the evening, all battery discharge again until it reaches the initial SOC level at the end of the day. Notice that the amount of charging is different from user to user as each user has different local demand and consumption shifting flexibility. Grid and local energy prices of each hour are illustrated in Fig. 4.10. The grid buying prices dynamically change depending on the total community consumption profile, and the price is peaked in the evening when the community demands the highest energy from the grid. The local selling and buying prices lie between the grid prices to incentive the users to share their energy within the community. When the local energy surplus is high during the day, the local energy prices drop near the grid selling price limit while, during morning and evening periods, only energy from batteries is shared among users resulting in local prices rising toward grid buying price level. Lastly, the convergence of the proposed *LES+DGP* is shown in Fig. 4.11. The total energy bills reduce dramatically until the 100th iteration and continue slightly decreases until saturating around 200th iteration, reaching the convergence, and the algorithm is terminated. All users' HEMSs reach the optimal consumption schedules, and the final energy prices are settled.

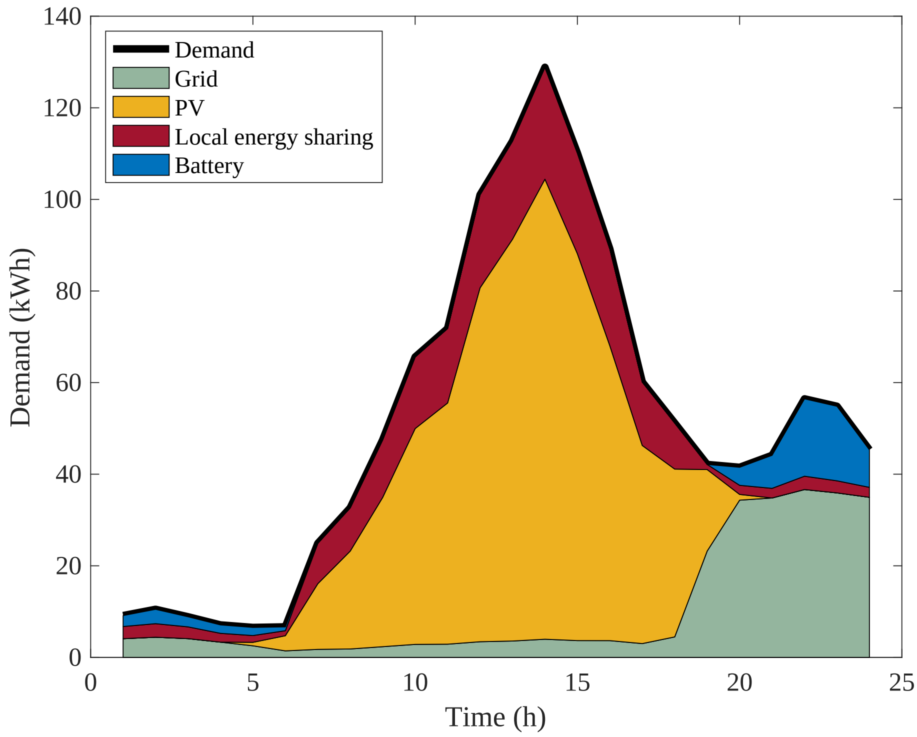

Figure 4.8: Demand curve and the corresponding sources of energy in the proposed *LES+DGP* case

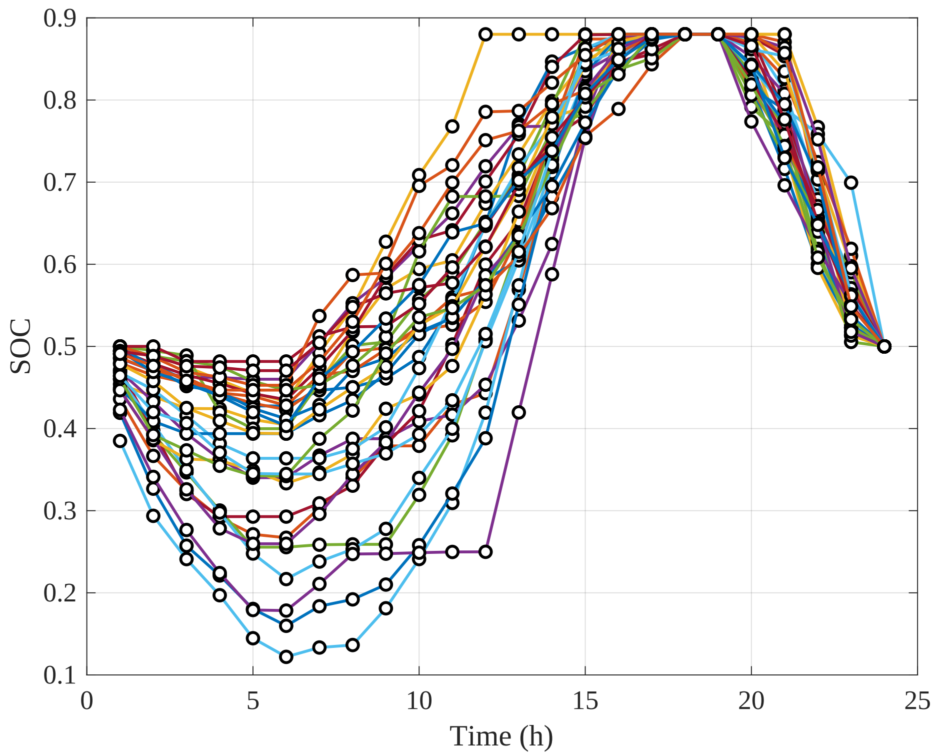

Figure 4.9: Battery's SOC level of all users equipped with battery system in the community

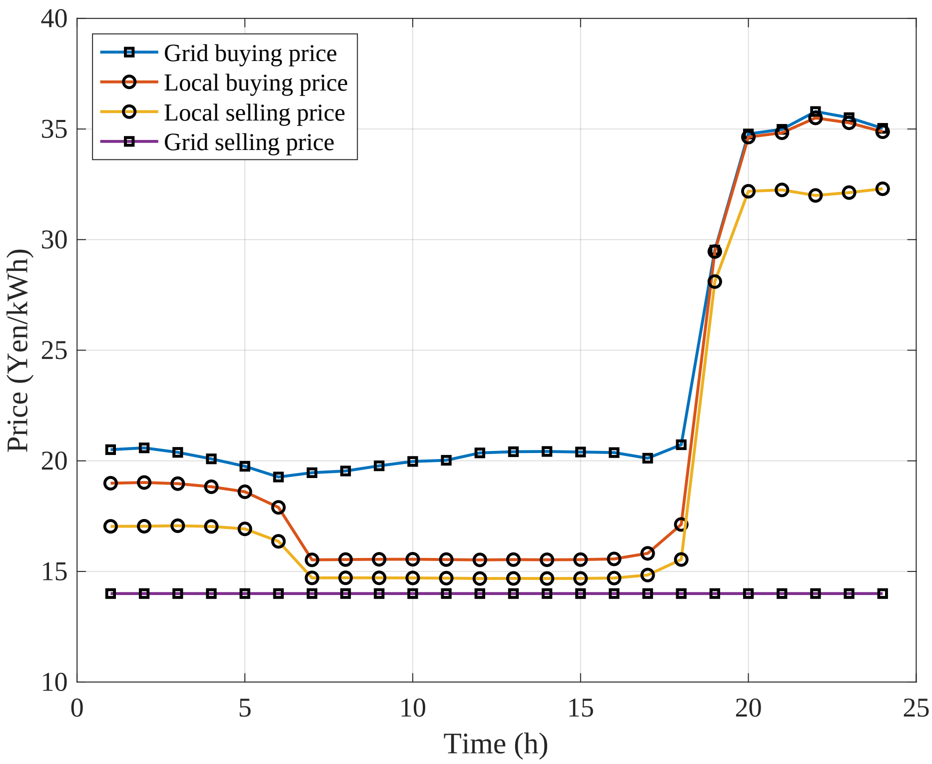

Figure 4.10: Grid and local energy prices

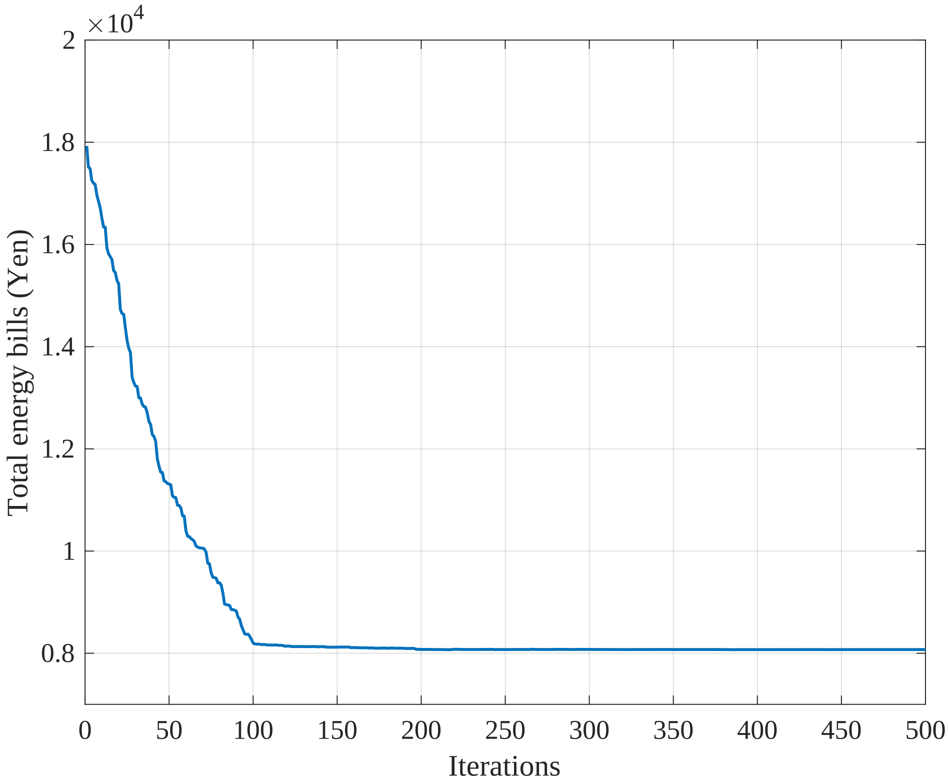

Figure 4.11: Convergence of the proposed *LES+DGP* case

4.4.7 Analysis of Computation Time and Convergence

In this section, we analyze a computation time of the proposed consumption scheduling for each house and convergence test of the algorithm 1. We use a computer with 2.9 GHz Quad-Core Intel Core i7 with 16 GB memory as a testing environment. Fig. 4.12 shows a computation time of individual house equipped with a battery for a different number of flexible appliances from 1 to 15. The computation time rapidly increased as the number of flexible appliances increased since more variables are needed to be optimized. Fig. 4.13 shows a number of iterations required for algorithm 1 to converge to the optimum solutions with a different number of houses in the community. From the convergence results, we can see that the algorithm converges in less than $4N$ iterations, where N is the number of houses in the community, in all simulation runs.

From the computation time and convergence test results, we determine the practicality of the proposed algorithm by analyzing an extreme case where all houses in the community are equipped with a battery and $4N$ iterations are required for convergence. Fig. 4.14 shows an estimation of a number of houses in the community where computation time of the algorithm reaches 24 hours in the extreme case, which is assumed to be the maximum limit for scheduling day-ahead energy consumption. In a case where each house has 1 flexible appliance, the number of houses is limited to 36,080. The maximum number of houses declined as the number of flexible appliances increases. For 5, 10, and 15 flexible appliances per house, the number of houses in the community is limited to 6,100, 1,313, and 360, respectively. Thus, we conclude that the proposed algorithm is applicable to a community with the size of thousands of houses and up to 10 flexible appliances per house. Note that the computation time could be improved by increasing computation power, e.g., using cloud computing service with more computation power. Another way to speed up the computation time is to redesign the algorithm and apply the divide and conquer technique with parallel computing, which is considered in future work.

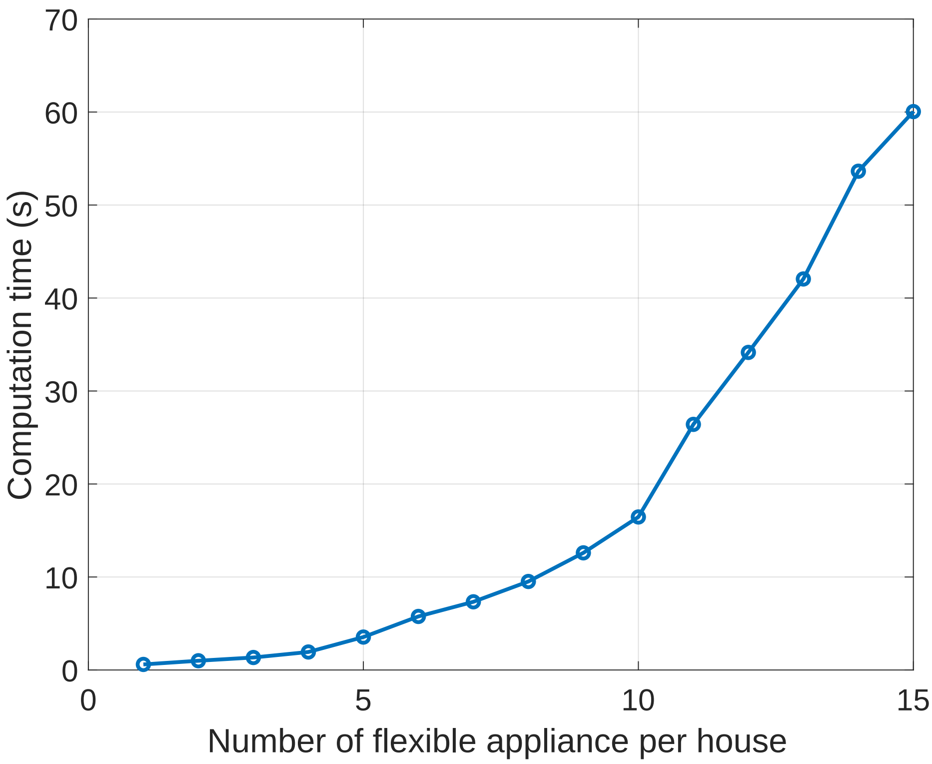

Figure 4.12: Computation time of individual house per number of flexible appliances

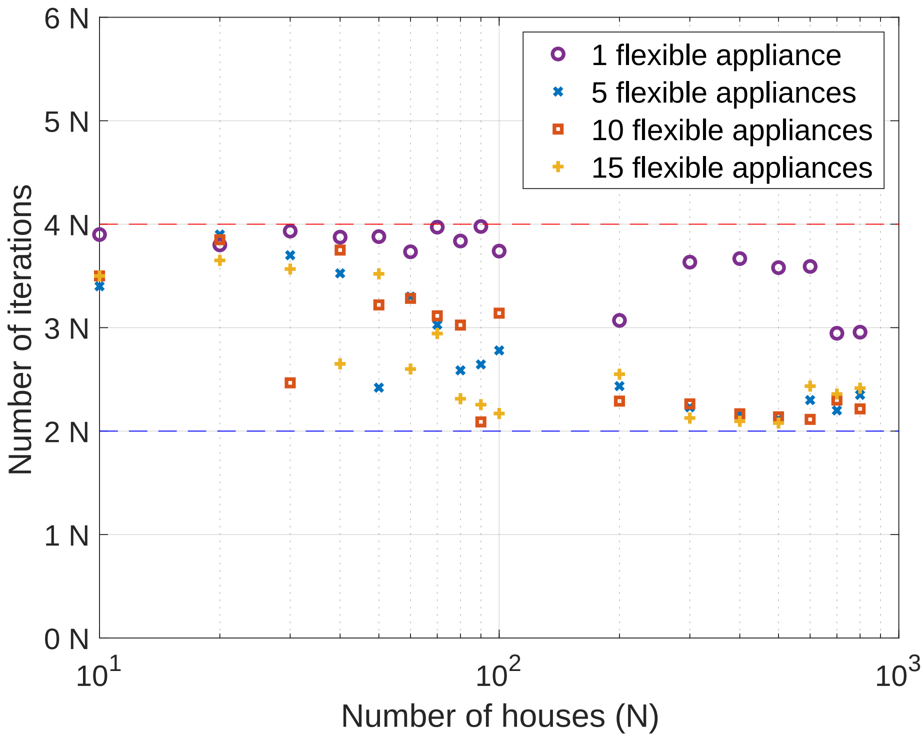

Figure 4.13: Number of iterations required for convergence

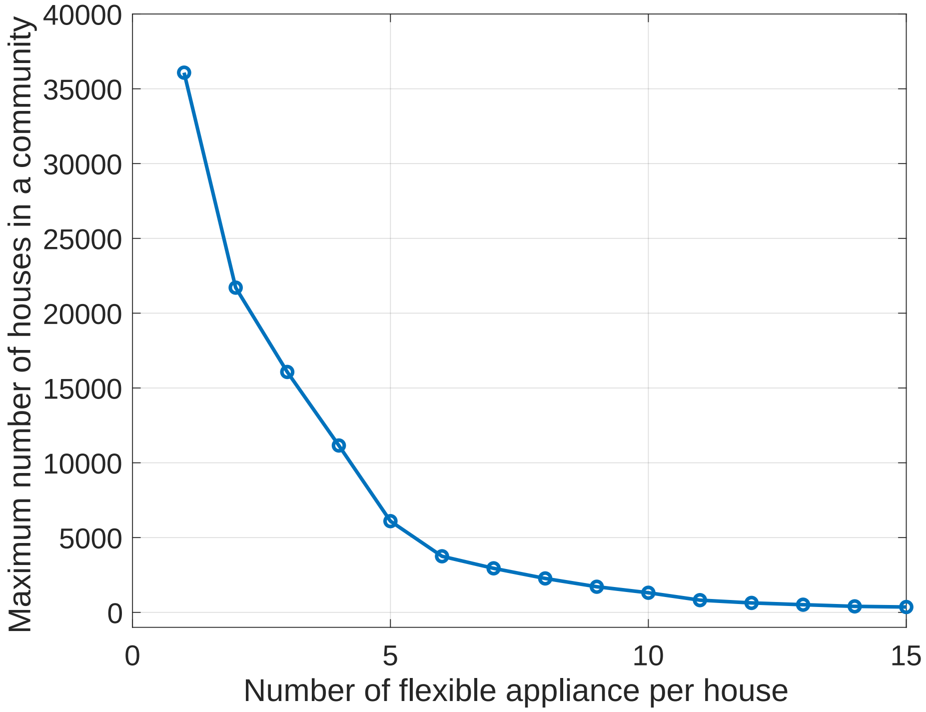

Figure 4.14: Maximum number of houses in the community for the extreme case

4.4.8 Performance with Various Numbers of Users with Battery Storage Systems

In practice, the users who purchase a household PV system might not always equip with a battery storage system. However, as the price of battery continues to decline, it is expected that more customers, in the near future, will choose the PV-battery solution for their DER systems. To evaluate the impact of battery systems in the community, a study was carried out considering different numbers of PV-battery owners in the community. The number was varied from 0% to 100% (with an increment of 20%). 0% means all users only equipped with PV generation without battery storage. On the other end, 100% means all users are equipped with the PV-battery system. Table 4.3 presents the system performance metrics of the study.

Table 4.3: System assessment metrics with different percentage of PV-battery system owners

Percentage of PV-battery system owner (%)	Total community energy bill (Yen)	Self-consumption rate (%)	Self-sufficiency rate (%)	Peak demand (kWh)	PAR	Total export energy (kWh)	Total import energy (kWh)
0	9,934	87.32	72.88	55.37	7.11	119.42	306.11
20	7,774	95.81	79.32	43.01	5.26	39.39	235.40
40	6,272	100.00	82.35	31.55	3.74	0	201.95
60	5,427	100.00	81.96	23.22	2.68	0	207.33
80	5,028	100.00	81.63	15.68	1.77	0	211.98
100	4,977	100.00	81.40	11.86	1.32	0	215.28

Increasing the number of batteries decrease the total energy bills since more users can store PV energy and use it when the prices are high. However, the marginal bill saving decreases when there are moderate numbers of battery (40%) presented in the system as all PV generation has been utilized locally, resulting in fewer profits from energy sharing. Both self-consumption and self-sufficiency increase to 100% and 82%, respectively, around 40% of the users owning batteries. Increasing the numbers of battery beyond 40% has no significant impact on both self-consumption and self-sufficiency since the utilization of the local energy reached the maximum. However, peak demand and PAR continue to decline until 100% of the users have a battery. This is because each user, with battery storage, can suppress individual peak demand independently, leading to accumulating peak reduction of the community and improving PAR. In short, battery storage benefits the whole community in terms of bill and PAR reduction while total utilization of local generation can be achieved with a moderate number of the battery. A higher number of batteries can result in less marginal gain achieved when the local generation is wholly used up locally.

4.4.9 Performance with Various PV Generation

The amount of local energy generation, e.g., from PV, can cause the energy system several issues if not appropriately managed. The network voltage tends to rise, and temperature can reach the capacity limit if the power from PV is injected in the system too much. To evaluate the impact of local generation on the system, a study was carried out considering a different amount of daily PV generation per user in the community. The daily average PV production per user was varied from 0 to 11.78 kWh. All users are assumed to equipped with a PV unit, and 30% of the users also own battery storage systems. Table 4.4 shows the system performance of the study.

Table 4.4: System assessment metrics with different amount of PV generation

Average daily PV generation per user (kWh)	Total community energy bill (Yen)	Self-consumption rate (%)	Self-sufficiency rate (%)	Peak demand (kWh)	PAR	Total export energy (kWh)	Total import energy (kWh)
0	47,332	NA	0	52.75	1.11	0	1,137.60
2.35	32,871	100	20.72	40.90	1.08	0	901.06
4.71	21,341	100	41.44	38.12	1.37	0	665.88
7.06	12,725	100	62.08	36.72	2.04	0	431.69
9.42	6,938	98.68	81.46	36.66	4.41	12.41	211.56
11.78	3,507	79.43	81.97	36.72	24.09	242.27	205.69

We observe that as the amount of PV generation increases, the total energy bill decreases dramatically. This is the case since the users required less energy from the grid, and the demand can be fulfilled from the local generation. However, as the PV generation reaches a certain amount (from 9.42 kWh/user), community starts to export energy back to the grid as the system flexibility approaches the limit: load shifting and battery storage available in the community can only handle the PV generation up to a certain amount. Thus, the self-consumption rate drops below 100% in high PV generation. PAR also suffers from the raise of local supply, and the effect amplifies when export energy reaches a peak during mid-day since the difference of minimum and maximum community net consumption becomes larger. In short, the local generation benefits users in terms of bill saving, but the system can suffer from high PAR if there is a surplus of energy. System flexibility can help the system to maintain a good performance (self-consumption remains 100%) up to a certain level of PV generation before the community needs to export energy back to the grid and significantly raise PAR.

4.4.10 Performance with Various Numbers of Users Participating in the DSM Programs

The DSM programs required flexibility from the participation of individual users to achieve their desired outcomes. However, in practice, there might be a fraction of users in a community participating in the program, while others remain solely passive consumers. To evaluate the impact of user engagement in the program, a study was carried out considering different numbers of users participating in the proposed DSM program. We varied user participation percentage from 0% to 100% (with an increment of 20%). When there is no participating user (0%), all users become passive users without scheduling their energy consumption. When 100% user participation, all users schedule their consumption and trade their energy through the CEC with local energy sharing enable. Table 4.5 shows the system performance of the study.

Table 4.5: System assessment metrics with different user participation percentage

Participation percentage (%)	Total community energy bill (Yen)	Self-consumption rate (%)	Self-sufficiency rate (%)	Peak demand (kWh)	PAR	Total export energy (kWh)	Total import energy (kWh)
0	14,256	63.31	64.47	69.49	8.05	175.46	382.58
20	12,505	83.85	69.37	63.29	7.72	152.15	348.78
40	9,089	92.71	76.30	46.38	5.49	68.70	271.32
60	6,357	100	81.88	29.80	3.43	0	208.50
80	5,169	100	81.59	17.96	2.02	0	212.52
100	4,977	100	81.40	11.86	1.32	0	215.28

As the number of participating users increases, higher reduction of energy bills, peak demand, and PAR are observed. This is because more system flexibility can be exploited by active participants. The passive users also gain economic benefits even though they did not participate in the DSM program since the grid energy prices become lower as the community aggregate demand flattens. We also observe that, at a high participation rate (beyond 60%), the marginal gain of having more participants reduces when the system reaches 100% self-consumption. In short, the whole community can benefit from the DSM program at any participation rate: both active and passive users can enjoy bill saving while the system performance also improves. However, the marginal gain is reduced at a high participation rate as self-consumption already reached 100%.

4.5 Chapter Summary

In this chapter, we present a price-based DR with an integrated local energy sharing market for day-ahead consumption scheduling in a community with a high penetration of DERs. The proposed local energy pricing scheme is coordinated by the CEC, which incorporated the dynamic of grid price while also taking into account the aggregate users' local energy supply and demand. Energy consumption scheduling is formulated as the energy bill minimization problem which is solved through the iterative distributed decision-making algorithm, without revealing details regarding individual energy consumption, thus preserving user privacy. Simulation results show a mutually beneficial relationship between users and the utility company. The users achieved higher economic benefit when participating in the proposed DSM method compared to other existing methods. The utility company received a benefit from overall flatter community aggregate energy demand: lower peak demand and export energy. The better utilization of DER resulting in improving the community's self-consumption and self-sufficiency. Furthermore, the impacts of battery storage, PV generation, and user participation in the performance of the system have been analyzed. The publications related to this chapter can be found in the publication list [1] and [3].

Chapter 5

Consumption Rescheduling

In this chapter, we focus on addressing the research gap in DSM by considering the uncertainty of human behavior, which is difficult to predict. We make an assumption that the users' appliance preference might be changed after the day-ahead schedules have been computed. To accommodate such last-minute changes, we propose an energy consumption rescheduling algorithm to cope with the deviating users during the operation periods. The objective is to minimize the total energy bill by giving the users the option to request new schedules, which would also result in a reduction of peak demand and export energy of the aggregate energy consumption profiles. Simulation results demonstrate the effect of the human uncertainty on the system performance and verify the effectiveness of the proposed rescheduling algorithm when applied.

5.1 Energy Consumption Rescheduling Algorithm

In this section, we present the proposed energy consumption rescheduling algorithm to address any change of the user preference by allowing the user's HEMS to recalculate appliance consumption and battery operation schedules of the remaining hours.

The initial scheduling time horizon $\mathcal{H}$ that we consider for the day-ahead schedules via DSM starts at $h = 1$ and stop at $h = H$, with hourly time-slot. The "rescheduling algorithm" computes the consumption schedule on time horizon $\{t + 1, ..., H\}$, where t is the time-slot that a user request to change operation time preferences of his appliances. The rescheduling algorithm would be executed during time-slot t and finish before the starting of the next time-slot $t + 1$.

For better understanding, considering the following example: A user was preferred to operate a vacuum cleaner between 12:00 - 16:00 the next day. However, when the user wakes up in the morning at 8:00 and discovers that he has to go to his office in the afternoon due to an urgent meeting. Thus, he wants to change his preference for using the vacuum cleaner to 18:00 - 20:00 after he comes back home. So, he can set his new preference in his HEMS. Then, the HEMS automatically sends a request to the CEC. Before 9:00, the CEC starts a rescheduling process and sends community consumption information to the HEMS to find the best time for using the vacuum cleaner during 18:00-20:00.

Note that the user may have more than one appliance that he wants to reschedule the energy consumption plan for, and there may be more than one user who also wants to reschedule in each time-slot. Without any mechanism to provide the update consumption schedule, the user has no idea when to use the appliance during his new preferred periods and may use the appliance when the energy price is high. This could have a negative impact on the community consumption profile if many users change their energy consumption from the assigned schedule without considering the community consumption condition.

Let assume that a user $m \in \mathcal{M}$, where $\mathcal{M}$ is a set of users who request for rescheduling at time-slot $h = t \in \mathcal{H}$, has a set of flexible appliances $\mathcal{A}_m^{'} \in \mathcal{A}_m$ that need to recalculate its consumption schedules. For each appliance $i \in \mathcal{A}_m^{'}$, the associated time preference is changed from $[\alpha_i, \beta_i]$ to new time preference $[\alpha_i^{'}, \beta_i^{'}]$ by the user m. Note that only the appliance that its operation has not start before $h = t$ can be rescheduled. The energy constraints of the appliance i is updated with the new preference as

$$e_i = \sum_{h=\alpha_i^{'}}^{\beta_i^{'}} x_{m,i}^h, \forall i \in \mathcal{A}_m^{'}. \tag{5.1}$$

Each user $m \in \mathcal{M}$ recalculate his optimal consumption schedule of all appliances in the set $\mathcal{A}_m^{'}$ and battery operation at time t to minimize his daily energy bill for the remaining time horizon $\mathcal{H}^{'} = \{t+1, \ldots, H\}$ as in the following optimization problem:

$$\begin{aligned}
\underset{\mathbf{z}_m^{'} \in \mathcal{Z}_m^{'}}{\text{minimize}} \quad & B_m(\mathbf{z}_m^{'}) \\
\text{subject to} \quad & e_i = \sum_{h=\alpha_i^{'}}^{\beta_i^{'}} x_{m,i}^h, \forall i \in \mathcal{A}_m^{'} \\
& x_{m,i}^{h,min} \leq x_{m,i}^h \leq x_{m,i}^{h,max}, \forall h \in \mathcal{H}^{'} \\
& y_m^{min} \leq y_m^h \leq y_m^{max}, \forall h \in \mathcal{H}^{'} \\
& SOC_m^{min} \leq SOC_m^h \leq SOC_m^{max}, \forall h \in \mathcal{H}^{'} \\
& SOC_m^H = SOC_m^0
\end{aligned} \tag{5.2}$$

where $\mathcal{Z}_m^{'}$ is the updated set of feasible energy consumption for the user m respected to the constraints in (5.1), (3.2), (3.7), (3.8), and (3.9) and $\mathbf{z}_m^{'} \triangleq [x_m^{t+1}, x_m^{t+2}, ..., x_m^H, y_m^{t+1}, y_m^{t+2}, ..., y_m^H]$ is a decision vector containing energy consumption of the appliances in $\mathcal{A}_m^{'}$ and battery operation over the remaining scheduling period $[t+1, ..., H]$.

The rescheduling procedure for all users in $\mathcal{M}$ is coordinated by the CEC at any time-slot $t \in \mathcal{H}$, similar to the day-ahead scheduling algorithm in Chapter 4. The summary of the rescheduling procedure for each user is presented in Algorithm 2 and the following details. At any time-slot instant $t \in \mathcal{H}$, the CEC receives rescheduling requests from all users in $\mathcal{M}$. Then, the CEC randomly selects user $m \in \mathcal{M}$ to recalculate his energy consumption schedule according to (5.2) by providing the expected community energy consumption for the remaining time $\{t+1, ..., H\}$. The selected user's HEMS solves the optimization problem to minimize her remaining daily energy bill. Then, if the consumption schedule solutions different from the previous solution, the HEMS updates the community energy consumption information by substituting new solution with the previous one and announce it back to the CEC. Once the CEC received the update, it randomly selects the next user in $\mathcal{M}$ to reschedule. The process is repeated until the

CEC receives no update from the users and the algorithm is terminated. If the number of iteration reached a predetermined maximum limit, the final solutions are taken as in the last iteration. A flow chart of the rescheduling algorithm is shown in Fig. 5.1. Note that when a user's HEMS reschedules, the consumption schedules of other users $n \notin \mathcal{M}$ remain unchanged. The reason is that we want to minimize the impact of the rescheduling process to other users such that their consumption schedules remain the same as in the day-ahead schedules and not causing any frequent schedule change for the users that can promise to the schedules. However, the energy bills may be changed due to the local price functions that depend on the aggregate energy consumption of the community which would be realized in real-time. This energy bill discrepancy will be addressed in Chapter 6.

Algorithm 2 Consumption rescheduling: executed by HEMS of each user $m \in \mathcal{M}$

Input: z_m^*, L, E_s and E_b for $\{t+1, ..., H\}$
Output: Consumption schedule $\mathbf{z}_m^{*'}$
at any time-slot instant t
  update appliance i's preference to $[\alpha_i', \beta_i'], \forall i \in \mathcal{A}_m'$
  send request for rescheduling to the CEC
  repeat
    when receive execute command and L, E_s, E_b from the CEC
      solve local optimization problem (5.2) for $\mathbf{z}_m'$
      if $\mathbf{z}_m'$ *changes compare to the previous consumption schedule* ($\left\|\mathbf{z}_m' - \mathbf{z}_{m,prev}'\right\| \geq \epsilon$) **then**
        update L, E_s and E_b with the new $\mathbf{z}_m'$
        announce L, E_s and E_b to CEC
      end
until *no consumption schedule is updated or reach maximum iteration threshold*

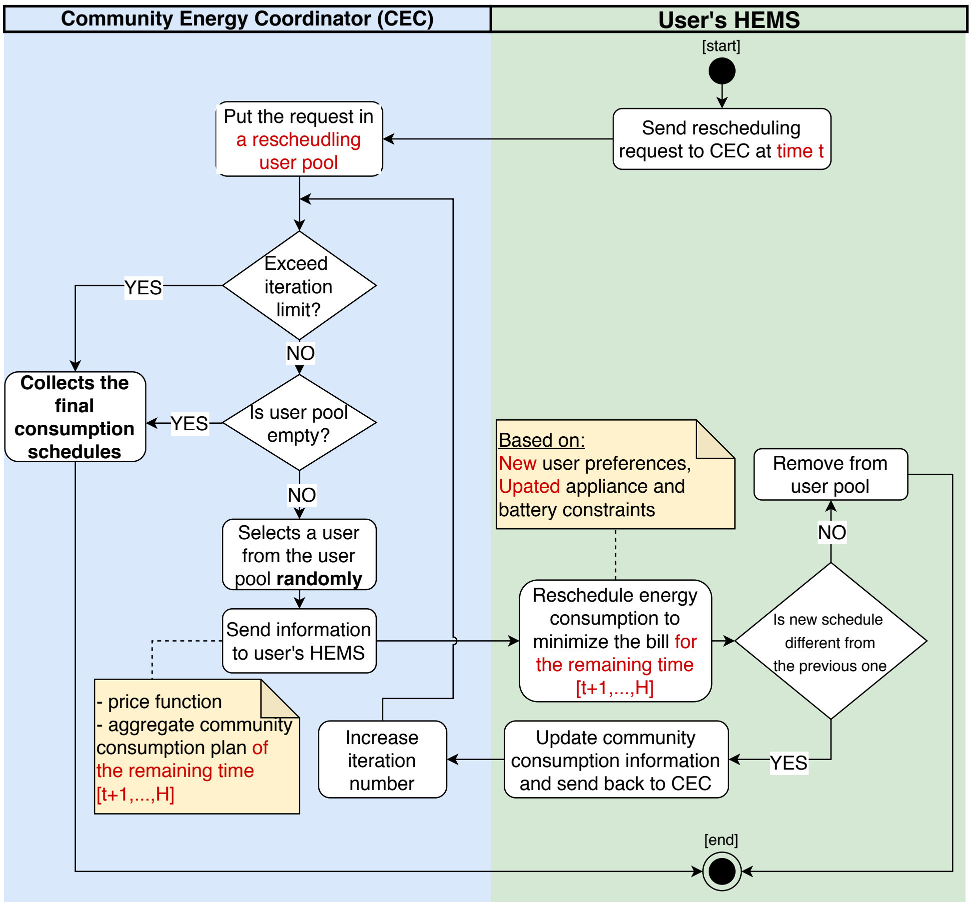

Figure 5.1: Flow chart of the proposed rescheduling algorithm

5.2 Simulation Results

In this section, we present a numerical comparison of our proposed energy consumption rescheduling algorithm with three other case scenarios as follows:

- The *uncoordinated P2G+OTS* case is defined as an original consumption profile of the users with an off-the-shelf battery control algorithm. In this case, no DSM is implemented to control or incentivize the users: the consumption profiles are taken as the observed values in the sampling data.

- The *perfect commitment* case is assumed that all users perfectly commit to the day-ahead optimal schedules when DSM is implemented and no consumption deviates from the day-ahead schedules.

- The *deviated schedule without rescheduling* case is assumed that users have changed their preferences without applying the rescheduling algorithm. The users will change the operation time of the appliances and use them as early as possible according to their new preferences.

- The *deviated schedule with rescheduling* case is assumed that the users have changed their preference and the proposed rescheduling algorithm is applied to recalculate new appliance consumption respect to their new preferences.

5.2.1 Simulation Setting

The simulation setting in this chapter is similar to the setting in the previous chapter. For completeness, we will briefly present the simulation setting in this chapter. In the simulations that follow, the CREST demand model [3] was used as the residential user demand consumption. This model is a high-resolution (one-minute resolution) stochastic model of domestic electricity demand that incorporates appliance composition, human occupancy model and electrical parameters derived from time-use survey data. In the simulations, a population of 100 households ($N = 100$) on one ordinary weekend day in summer was considered. Appliance types and power rating parameters, the human occupancy, and user demand were gathered by randomly sampling from the CREST model. Examples of non-flexible appliances (i.e., critical appliances that their energy consumption cannot be shifted and must keep the power level as the original schedules) include refrigerator, television, personal computer, and lighting. Flexible appliances, including dishwasher, washing machine, and electric shower, were modeled using (3.1) and (3.2). The full list of 31 appliances used in the simulation can be found in Appendix B. The number of appliances each user owns is determined by the result of sampling from a given probability distribution based on realistic statistics from a time-use survey. Note that not all appliances in the list are occupied by every user. We assumed the daily energy requirement for each appliance corresponds to the data sampled. For appliance energy constraints, we set $x_{n,i}^{h,min} = 0$ and $x_{n,i}^{h,max}$ equal to the maximum observed value. The user preferences in the day-ahead consumption scheduling are randomly assigned for each flexible appliance considering the original schedules within two hours. For the demonstration, the number of users who change their preferences and the corresponding appliances are randomly drawn from the uniform distribution for each time-slot from 5:00 to 18:00. Also, the new preferences for each appliance are randomly assigned after the time of the request t.

A lithium-ion battery specification is based on a small-scale household battery from sonnenBatterie eco 8.0 [83] with a capacity of 6 kWh. The battery has a one-way efficiency of 98% and an inverter efficiency of 96%. The SOC_n^{min} and SOC_n^{max} is set to 0.08 and 0.88, respectively. The maximum charging/discharging rates are 3 kW. The initial SOC of 0.5 is assumed for all users at the beginning of the scheduling period.

The coefficients of the grid buying price function are set as $a^h = 0.47$ and $b^h = 18.62$, $\forall h \in \mathcal{H}$. The grid selling price $p_{g,s}^h$ is set to be 14 JPY/kWh. The optimization in (4.12) and (5.2) were solved using MATLAB optimization toolbox. For the iterative distributed algorithm, we set $\epsilon = 0.01$ and maximum iteration number of 500.

5.2.2 Results of Consumption Rescheduling

Figure 5.2 shows the corresponding aggregated energy consumption of the community in different scenarios and we observe that the perfect commitment case performs the best with the lowest peak demand and the smoothest net energy consumption curves (as also shown in Chapter 4). This is because of the assumption of ideal user behavior which achieved the optimal performance given the available flexibility of the users. The result of the deviated schedule without rescheduling case suffered from the assumption of the uncertainty of human behavior, resulting in increased peak demand and export energy. With the proposed rescheduling algorithm, a peak demand and export energy can be reduced compared to the case where rescheduling is not applied. This is because of the rescheduling algorithm schedules devices in such a way as to minimize the user's energy bill by shifting the consumption from high price periods to low price periods. However, the

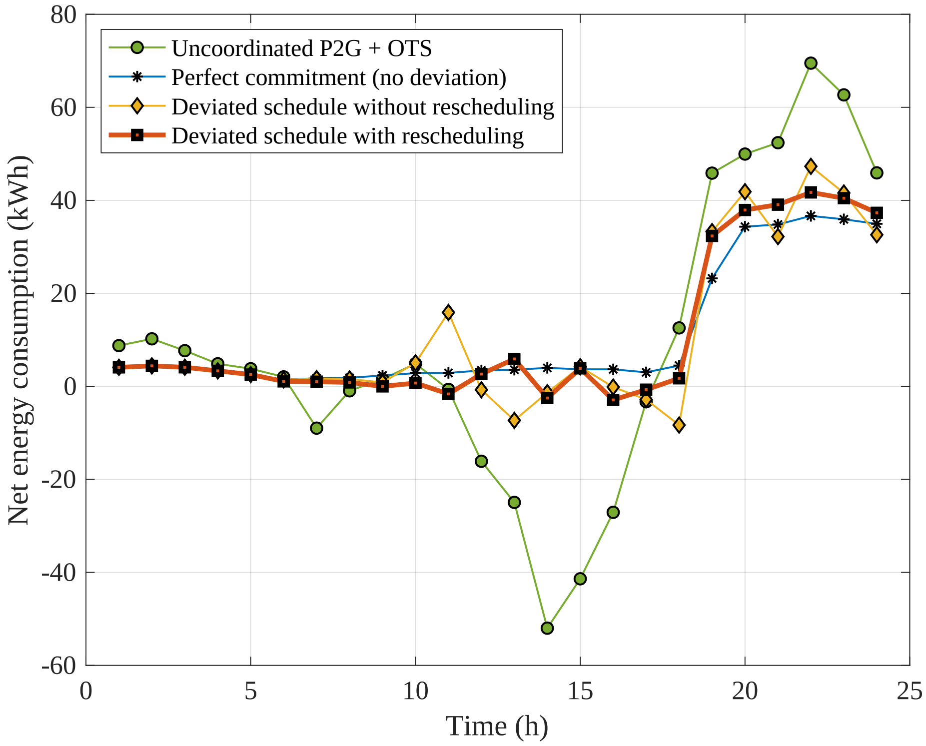

Figure 5.2: Aggregate net energy consumption profiles of 100 users in the case of uncoordinated P2G+OTS, perfect commitment, deviated schedule without and with rescheduling algorithm

available flexibility of the devices is lower than the day-ahead scheduling, the performance is not as good as in the perfect commitment case. The results also showed that when DSM is implemented we can still achieve better performance than the uncoordinated P2G+OTS case, even when we assume the uncertainty of the user's behavior.

A summary of the numerical results is shown in Table 5.1. The deviated schedules, both with and without rescheduling, lead to higher total energy bills and lower both self-consumption and self-sufficiency compared to the perfect commitment case. The case without rescheduling increases the total bill by 13.1% and increases both PAR and peak demand by 22.5% whereas both self-consumption and self-sufficiency decrease by 3.9% and 2.3%, respectively. With the proposed rescheduling algorithm, we can improve the system performance from the deviated schedule without rescheduling algorithm: 3.0% decrease in total energy bill, 11.8% decrease in both PAR and peak demand, 3.0% increase in self-consumption, and 1.5% increase in self-sufficiency. In short, with the rescheduling

Table 5.1: System performance comparison of uncoordinated P2G+OTS, perfect commitment, deviated schedule without and with scheduling algorithm cases

Case scenario	Total community energy bill (Yen)	Self-consumption rate (%)	Self-sufficiency rate (%)	Peak demand (kWh)	PAR	Total export energy (kWh)	Total import energy (kWh)
Uncoordinated P2G+OTS	14,256	63.31	64.47	69.49	8.05	175.46	382.58
Perfect commitment	8,068	100	77.45	36.65	3.42	0	257.19
Deviated schedule without rescheduling	9,294	96.11	75.63	47.30	4.41	20.73	277.91
Deviated schedule with rescheduling	9,012	99.12	76.76	41.70	3.89	7.78	265.02

algorithm, the system performance would always be improved from the deviated schedule without rescheduling case. However, the amount of performance improvement of the rescheduling algorithm significantly depends on variables such as the request rescheduling time and new preference periods, the number of rescheduling users, and the number of rescheduling appliances.

5.3 Chapter Summary

In this chapter, we proposed energy consumption rescheduling algorithms for the DSM programs. We considered the implications of allowing users to deviate from their original preferences and request new energy consumption schedules that are different from the assigned day-ahead optimal schedules. The rescheduling algorithm recalculates the deviating user's schedule to find the best possible consumption schedule that minimizes the users' energy bills. Simulation results confirmed that the proposed rescheduling algorithm reduces the total energy bills of the community from the deviated day-ahead schedules by adaptively rescheduling user loads in response to their changing preferences. By being able to address changes in user preferences, the proposed algorithms will further help DSM programs to achieve a practical deployment in the future smart grid. The publications related to this chapter can be found in the publication list [2], [5] and [6].

Chapter 6

Fair Billing Mechanism

In this chapter, we focus on addressing the fairness issue of energy billing in the DSM when consumption schedules are violated from the assigned schedules. When users deviate their consumption, the realized energy prices change from the expected prices, which in turn, affects the energy payments of all other users in the community. To cope with unfair energy pricing, we propose an alternative energy billing mechanism that allocates any billing discrepancy to users based on their amount of deviated consumption, which indicated by the proposed penalty and reward factors. The simulation results are demonstrated to confirm the feature of the proposed billing mechanism.

6.1 Energy Billing Mechanism

In this section, the details of the proposed energy billing mechanism are explained. As mentioned in Chapter 4, the energy bill is calculated by the CEC for all users in the community at the end of each day for the amount of energy he consumed or sold. In the ideal scenario, a full commitment of users to their assigned consumption schedules is assumed. This assumption is based on the fact that violating the assigned schedules would decrease the economic benefit of the users and, thus, no reason for the users to violate the schedules. However, in practice, the ideal assumption rarely holds true due to various sources of uncertainty, e.g., load and generation forecast errors, change in human behavior, and unexpected events. Those violations from users would alter the aggregate community energy consumption profiles and consequently alter the realization of the energy prices. The change in energy prices will have an effect on the user's energy bill not only to the users who deviated the assigned schedules but also the users who committed to their assigned schedules. Hence, the situation is unfair to those committed users who expect a certain amount of bill savings or revenue.

6.1.1 Energy Bill Difference

To address the energy bill discrepancy, we proposed a fair billing mechanism using penalty/reward systems to proportionally allocate any bill difference to the users regarding the amount of energy deviation. Let define B^h_{RL} as the total community realized energy bill in hour h:

$$B^h_{RL} = \sum_{n=1}^{N} b^h_{n,RL} = \sum_{n=1}^{N} l^h_{n,RL} \cdot p^h_{l,RL} \tag{6.1}$$

where $l^h_{n,RL}$ is the actual load of user n in hour h and $p^h_{l,RL}$ is the corresponding realized local energy price. Note that the CEC needs to collect the daily payments $B_{RL} = \sum_{h=1}^{H} B^h_{RL}$ from the users for the amount of energy they consumed or sold and pay to the utility company.

Since the day-ahead local energy price, denoted by $p_{l,DA}$, is determined by the coordination of all users in the community, the users have the expectation that this price will be realized when calculating their energy bills. However, due to schedule deviation, the realized energy prices could differ from the expected prices ($p_{l,RL} \neq p_{l,DA}$). The energy bill difference causes by changing energy prices, in hour h can be calculated as

$$\Delta B^h = \sum_{n=1}^{N} l^h_{n,RL} \cdot p^h_{l,RL} - \sum_{n=1}^{N} l^h_{n,RL} \cdot p^h_{l,DA}. \tag{6.2}$$

Thus, to enforce fair billing, the energy bill difference will be the responsibility of the users who did not commit to their assigned schedules.

6.1.2 Penalty and Reward Factors

In order to fairly allocate the bill difference to the responsible users, we define the cause of schedule deviation into two types as follows:

- *Deviation from sudden violation* is caused by the user who suddenly increases or decreases consumption level from the assigned schedule without any notification to the CEC. This type of deviation is undesirable and has a negative impact on the overall system.

- *Deviation from the rescheduling process* is caused by the user who changed his preference and requested the CEC to recalculate his consumption schedule (proposed in Chapter 5). This type of deviation is less severe to the system since the consumption is allocated optimally according to the new preference.

Furthermore, we defined the penalty and reward factor for any user n and hour h as follows:

- The *penalty factor* Θ_n^h indicates the degree that user n deviates from the assigned schedule compare to all other users in the community. The sum of penalty factors in each hour is one.
$$\sum_{n=1}^{N} \Theta_n^h = 1 \tag{6.3}$$

- The *reward factor* Ω_n^h indicates the degree that user n commits to the assigned schedule compare to all other users in the community. The sum of reward factors in each hour is one.
$$\sum_{n=1}^{N} \Omega_n^h = 1 \tag{6.4}$$

Let define the total amount of energy deviation of user n in hour h, denoted as Δl_n^h, consists of a sum of deviation from sudden violation $(\Delta \tilde{l}_n^h)$ and rescheduling process $(\Delta \hat{l}_n^h)$ as

$$\Delta l_n^h = \Delta \tilde{l}_n^h + w \Delta \hat{l}_n^h \tag{6.5}$$

where we introduce *a load deviation weight* $w > 1$ to weigh the amount of energy deviation from the sudden violation more than the deviation by the rescheduling process, since from the system perspective the violation of the assigned schedule is undesirable than the deviation from the rescheduling process. The value of w can be set by the system operator, depending on how much he valued the severity of the sudden schedule violation. Finally, the penalty and reward factors can be calculated as in the following equations, respectively:

$$\Theta_n^h = \frac{\Delta l_n^h}{\Delta L^h}, \tag{6.6}$$

$$\Omega_n^h = \frac{\Delta l_{max}^h - \Delta l_n^h}{\sum_{n=1}^{N}(\Delta l_{max}^h - \Delta l_n^h)} \tag{6.7}$$

where $\Delta L^h = \sum_{n=1}^{N} \Delta l_n^h$ is the total energy deviation in hour h and $\Delta l_{max}^h = max(\Delta l_1^h, ..., \Delta l_N^h)$ is the maximum energy deviation from a single user in hour h.

6.1.3 Proposed Billing Function

The proposed billing mechanism allocates penalty or reward to the users in the community when calculating their energy bills on an hourly basis. There are two billing cases, depending on the value of ΔB^h in each hour.

1. When $\Delta B^h > 0$:

   In this case, the CEC allocates the extra cost of energy to user n based on his corresponding penalty factor as

$$b_{n,prop}^h = l_{n,RL}^h \cdot p_{l,DA}^h + \Theta_n^h \cdot \Delta B^h. \tag{6.8}$$

2. When $\Delta B^h \leq 0$:

   In this case, the CEC allocates the extra revenue of energy to user n based on his corresponding reward factor as

$$b_{n,prop}^h = l_{n,RL}^h \cdot p_{l,DA}^h + \Omega_n^h \cdot \Delta B^h. \tag{6.9}$$

Finally, the total energy bill in each hour can be calculated from the sum of users' energy bills as

$$B^h_{prop} = \sum_{n=1}^{N} b^h_{n,prop}. \tag{6.10}$$

Note that amount of energy bill B^h_{prop} in each hour h is equal to the realized energy bill B^h_{RL} and only different in how the energy bill of individual user is allocated.

An example of the proposed billing mechanism is shown in Fig. 6.1, where energy bills of rescheduled, violated, and committed users are illustrated when the penalty is applied ($\Delta B^h > 0$). For demonstration, we set the same amount of energy deviation for both rescheduled and violated users. In Fig. 6.1, since committed users did not receive any penalty, their energy bills remain the same as in the expected day-ahead energy bills, while the users who deviate their assigned schedules have their bills increased (both rescheduled and violated users). Also, since the violated users subject to more penalty than the rescheduled users, the energy bills of the violated users are higher than the rescheduled users.

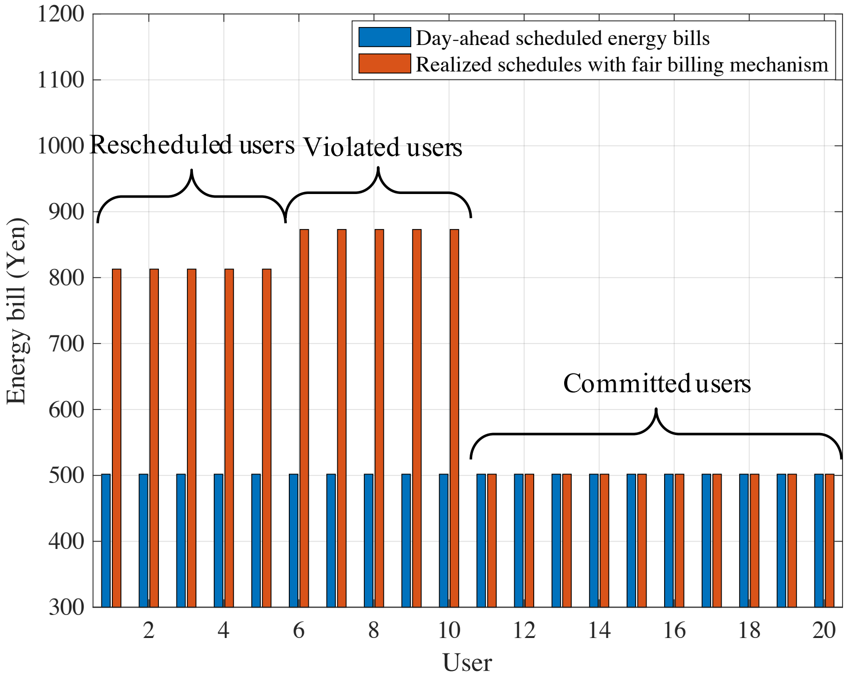

Figure 6.1: Example of the proposed billing mechanism

6.1.4 Fairness Index

In order to assess the fairness of the proposed energy billing mechanism, we define the fairness index F based on similar concept in [67,90] as the variance in the deviated energy consumption to energy bill difference ratios of users, which is expressed as follows.

$$F = \frac{1}{N}\sum_{n=1}^{N}\left(\frac{\Delta l_n}{\Delta b_n} - \frac{1}{N}\sum_{n=1}^{N}\frac{\Delta l_n}{\Delta b_n}\right)^2 \tag{6.11}$$

$$\Delta l_n = \sum_{h=1}^{H}\Delta l_n^h \tag{6.12}$$

$$\Delta b_n = b_n^* - b_{n,DA} \tag{6.13}$$

where Δl_n is the total amount of deviated energy consumption of the user n from the assigned day-ahead consumption schedule. Δb_n is the total energy bill difference of user n, $b_{n,DA}$ and b_n^* is expected day-ahead energy bill and realized energy bill of user n, respectively.

From 6.11, a lower fairness index F indicates a more fair billing. $F = 0$ means all users are allocated energy bills exactly proportionally to their deviated energy consumption. Larger values of F means that users are allocated with more or less energy bill than their "fair value" of schedule commitment.

6.2 Simulation Results

In this section, we present a numerical comparison of the proposed energy billing mechanism with the conventional energy billing mechanism. The demonstrating case scenarios are defined as follows:

- The *day-ahead scheduled energy bill*: Energy bills, in this case, are calculated as the expected energy bills when users schedule their consumption in the day-ahead scheduling process. Ideally, if no schedule is violated, the realized energy bills at the end of the day would be the same as the expected energy bills.

- The *conventional billing*: In this case, no penalty/reward system is implemented. The realized energy bills are calculated from realized energy prices after the users violated their schedules as

$$b_{n,conv} = \sum_{h=1}^{H} l_{n,RL}^{h} \cdot p_{l,RL}^{h}. \tag{6.14}$$

- The *proposed billing*: In this case, the penalty/reward system is applied to allocate any energy bill difference to the users proportionally. the realized energy bills are calculated using the proposed billing mechanism after the users violated their schedules as

$$b_{n,prop} = \sum_{h=1}^{H} b_{n,prop}^{h}. \tag{6.15}$$

6.2.1 Simulation Setting

In the simulation that follows, we consider the community in which the setting is based on previous chapters. We limit the population in the community to 20 users to demonstrate the effect of the penalty/reward system in the proposed energy billing mechanism. In each case scenario, we select users 1-5 to be “rescheduled users”, user 6-10 to be “violated users”, and user 11-20 to be ”committed users”. We assumed that the day-ahead scheduling and rescheduling processes of all users are finalized and all consumption demand has been realized as in Chapter 4 and 5. The amount of consumption deviation of rescheduled and violated users are randomly selected from a uniform distribution in the range of [0, 0.5] kWh in each time slot. The load deviation weight w is set equal to 2.

6.2.2 Results of the Proposed Billing Mechanisms

Figure 6.2 shows the impact of the users’ consumption deviations on the energy bills with conventional billing mechanism. We observe that the energy bills differ from the expected day-ahead bills because of the deviated consumption of the rescheduled and violated users. Despite the commitment to the allocated schedules, some of the energy bills of the committed users have been increased. Those users are unfairly charged with extra cost for unused energy. The unfairness in billing could undesirably influence the users' contribution and involvement in the DSM program. To promote fairness in billing, the results from the proposed billing mechanism is shown in Fig. 6.3. All the committed users received the rewards for their commitment and, thus, reducing their energy bills. On the other hand, the rescheduled and violated users received penalties and, thus, have their bills increase compare to the conventional billing mechanism. The corresponding deviated consumption and penalty/reward are shown in Fig. 6.4. By applying the proposed billing mechanism, the same proportion of rewards are allocated to each committed user because they are all perfectly followed the schedules. Moreover, since the penalty factor for each user is proportional to the amount, time, and type of deviation, the proposed billing mechanism also maintains fairness among the users who deviate consumption. Furthermore, with the same amount of deviated energy, the violated users received more penalty than the rescheduled users according to the weight w.

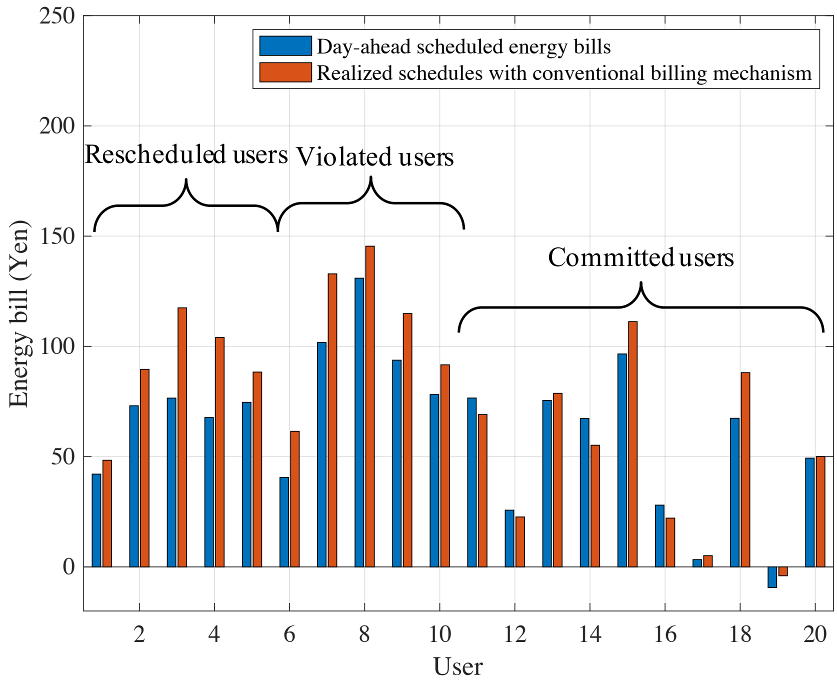

Figure 6.2: Energy bills of users with the conventional billing mechanism

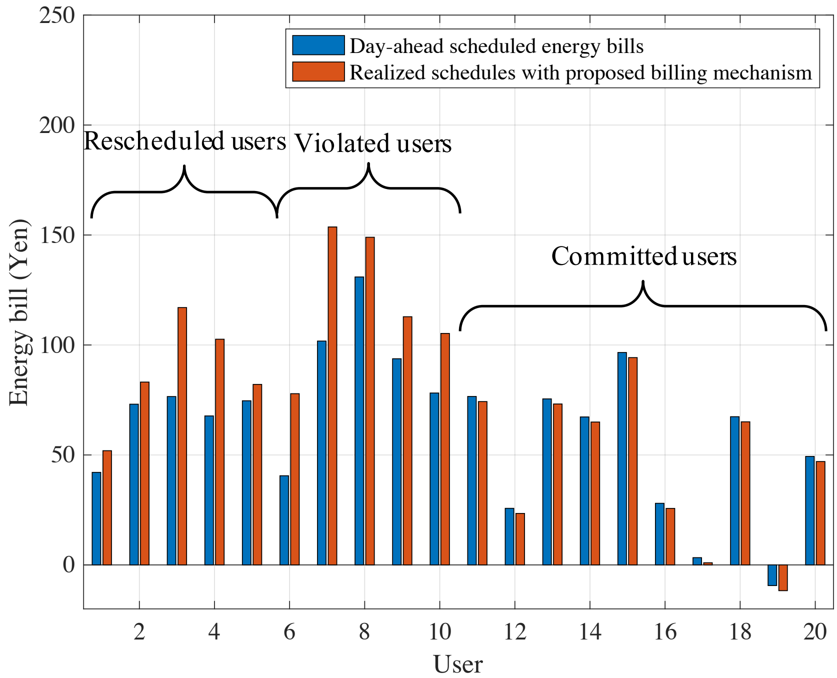

Figure 6.3: Energy bills of users with the proposed billing mechanism

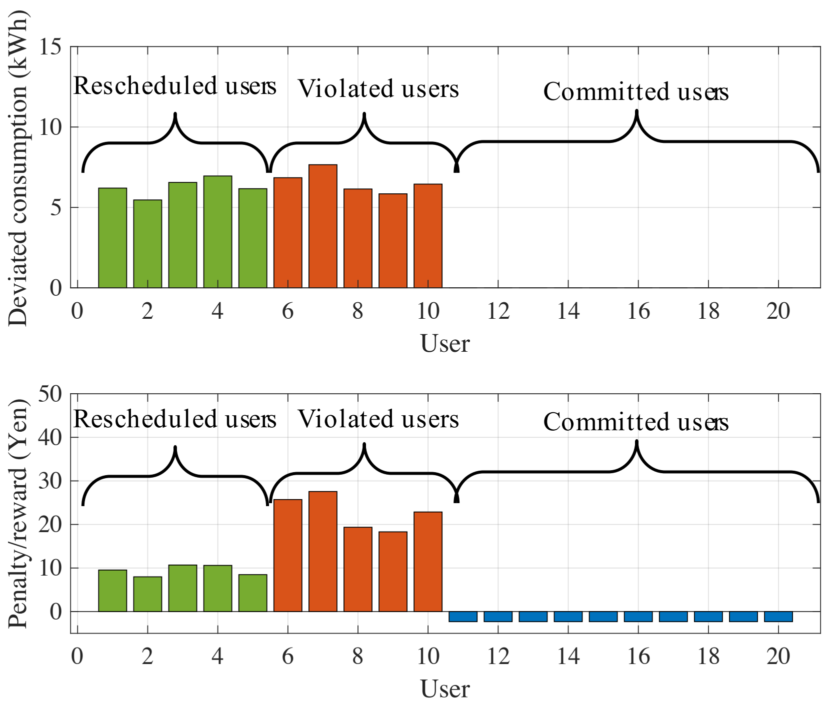

Figure 6.4: The corresponding deviated consumption and penalty/reward cost

Table 6.1 shows a comparison of the fairness index between conventional and proposed billing. As expected, the proposed billing achieved a lower value of F than the conventional billing method, which indicates that the energy bills are proportionally allocated to the users based on their consumption behavior.

Table 6.1: Comparison of fairness index

Billing method	Conventional billing	Proposed billing
Fairness index (F)	0.5655	0.0382

6.3 Chapter Summary

In this chapter, we proposed the alternative billing mechanism for DSM which fairly allocates energy bills to each user based on schedule deviation and commitment. The proposed billing utilized the penalty and reward factors based on a user's realized consumption level compared to the consumption level promised in the assigned day-ahead schedules. Users that commit to the schedules are protected from an increase in energy bills due to schedule deviation by other users and possible to receive economic incentives. For users that deviate their consumption, the proposed billing mechanism ensures the calculation of each user's payment based on their behavior and deviated consumption level. Thus, the proposed billing mechanism improved the level of billing fairness and expected to motivate users to continue participating in DSM and commit to the optimal day-ahead consumption schedules, which will further help DSM programs to achieve a practical deployment in the future smart grid. The publications related to this chapter can be found in the publication list [2] and [4].

Chapter 7

Discussions

In this chapter, we discuss a potential application of the proposed DSM method in the future of the electrical grid. We envision that the future of the electrical grid structure would change from top-down to bottom-up operation approach such that the profusion of DERs can be managed more efficiently. In the following, we explain the detail of our vision of the future grid and the impact on our society.

7.1 Toward Decentralized Layered Grid Structure

In the future bottom-up grid structure, the grid operation is divided into a layered structure: each layer would be responsible for its own optimization and reliability. The transmission layer, operated by TSOs, and distribution layer, operated by DSOs, would coordinate with each other via a single point of contact.

Moreover, inside the distribution layer, it could have another layer beneath it where the relationship between TSO and DSO is replicated. For instance, microgrids or communities of energy end-users could form a sub-layer, optimize their own energy usage, and communicate with that first distribution layer. Again, inside each microgrid and community, a sub-layer could be formed from smaller end-users and DERs cluster, e.g., households, solar panels, batteries, buildings. The process can be replicated until reaches the edge of the grid. All of the sub-layer is responsible for itself and interacts with the layer above via a single point of contact. In this way, the responsibility for the entity which operates each layer is decomposed to the layer beneath. Each layer interacts with the layer above or below and only responsible for itself. As a result, the bottom-up structure reduces the complexity of the grid, where no single entity needs to track and manage a vast number of DERs. Furthermore, the layered gird structure opens up a possibility for a distribution-level energy market, e.g., a local energy market that would aggregate DER offer to the upper-level wholesale market, obtain support services from DER, and enable local energy sharing within a given layer or even across adjacent layers. Each layer in the distribution network will have a smart controller maximizing its efficiency and only seek power from the upper layer when necessary. This would shifts the priority of big centralized power plants to the last and mainly reserved for backup power. Fig. 7.1 shows the envision the decentralized layered structure of the electrical grid with DERs.

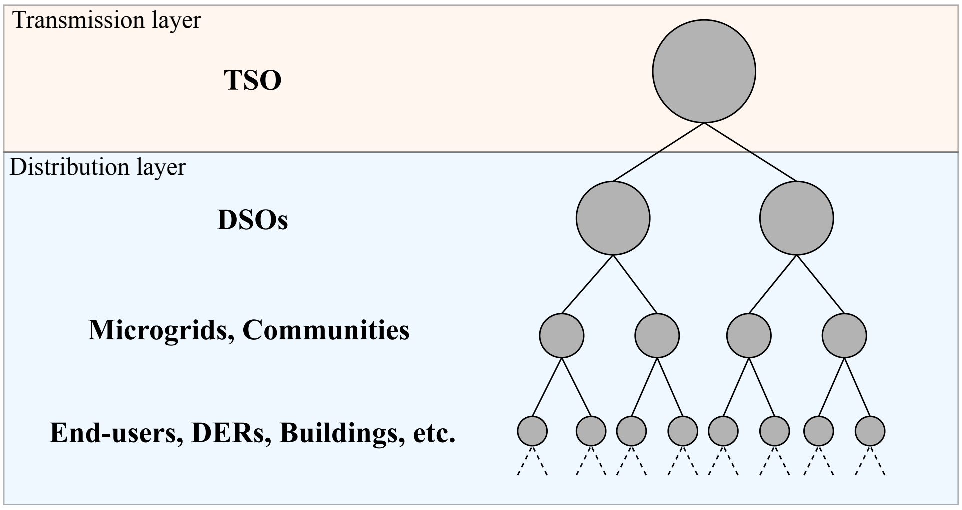

Figure 7.1: A conceptual diagram of the decentralized layered grid structure

Our proposed DSM model can be applied at the bottom layer of the grid, where DERs are located, and can be seen as one of the ways to manage a single layer (the residential community) with the interaction to the layer above (the utility company). Inside the considered layer, local demand and supply are optimized by a representing entity (the CEC) with local energy markets. We showed that the aggregate consumption curves could be flattened and yield substantial cost saving by creating incentives and requirements to shape the demand and manage the DERs locally.

7.2 Impact on Key Actors

The decentralized layered grid structure supports our electrical grid objectives to reduce environmental impacts, which includes electrification with clean energy and increased capability for end-user to choose and control their energy sources. However, building the grid from the bottom-up required many adaptations from all parties involved.

For the supply-side, the business model and structure need to be changed in order to serve new services from DERs. Traditional power generation will continue to exist but in a smaller scale. This eliminates the necessity for future investment in new power plants. The business model of the supply will shift its focus to new energy services rather than just delivering energy to customers. The invention that focuses on sustainable and environmentally friendly business models is necessitated.

The majority impact would be on the demand-side. End-users will need to change their habit and mindset in energy consumption. They will be more aware of how and when they consume their energy. Breaking from traditional habits, they need to adapt to a new lifestyle by efficiently plan their energy consumption to match with local energy supply. Local market design with incentives will motivate the end-users to participate in the local optimization. Home automation will be the primary technology to facilitate the users to control and optimize their energy plan without requiring too much attention from the users. Users can set their goals and preferences once and let their HEMS do the rest. Once in a while, the users may revise their energy usage performance and adjust their target if necessary.

With cooperation among energy users from the grid edge and hierarchically grid operations, sustainable energy practice could be achieved. Dependent on fossil fuel and large centralized power plants will be reduced, and energy responsibility will be decomposed to each of the grid layers with its own objective and operation. DERs will provide a better alternative source of energy with cleaner and more efficient than the traditional one. The decentralized layered grid structure will pave the way for managing the complex grid, speeding global decarbonization, and enhancing local resilience to overcome the world energy crisis and fight against climate change.

Chapter 8

Conclusions and Future Work

8.1 Conclusions

This dissertation proposed a DSM method to efficiently manage the energy consumption of users in a residential community with a high penetration of DERs. The main objective is to flatten the community consumption profile by reducing peak demand and the amount of export energy through the proposed energy pricing in the local energy sharing market. The proposed DSM model consists of three sequential procedures: day-ahead consumption scheduling, consumption rescheduling, and energy billing process.

In the proposed day-ahead consumption scheduling, we introduced the community energy coordinator to facilitate local energy sharing among users and responsible for the local energy market and balancing community supply and demand. The local energy prices are proposed as a function of the dynamic of grid energy prices and local supply and demand. The users are incentivized by scheduling their energy consumption and battery operation for the next day in order to minimize their electricity bills. The bill minimization problem is formulated for each user, which subject to preference, energy requirement, and device specification. The day-ahead consumption schedule of all users is then solved using the iterative distributed decision-making algorithm to preserve the information privacy of individuals. Simulation results showed a reduction in peak demand and export energy of the community consumption profile while maximizing users' energy bill savings. Also, the impact of battery, PV generation, and user participation on the system performance is studied and analyzed.

The consumption rescheduling process is used to address the uncertainty of human behavior. We made the assumption that users may change their preference, even the day-ahead consumption schedules are finalized. This could have a negative impact on the overall system if the users change their appliance consumption without considering the community consumption profile. Therefore, we proposed the consumption rescheduling algorithm to allow the users' HEMSs to recalculate their consumption schedule for the remaining time by request current community consumption status from the CEC. Simulation results showed a better aggregate consumption curve than the scenario where the uncertainty of human is overlooked.

Finally, we proposed the energy billing mechanism, which addresses the fairness issue in DSM due to consumption deviation from the assigned schedule. Since energy prices depend on total community consumption and local supply and demand, schedule violations would affect the energy prices. Fairness in users' energy bills is one of the most important factors to encourage users to contribute in the DSM programs. To fairly bill each user, we proposed the penalty/reward system, which allocates any energy bill discrepancy to each user based on the amount of violated consumption. We also considered a type of consumption deviation and penalized more on the users who violate their consumption suddenly. Simulation results showed a fair allocation of electricity bills to each user based on their consumption behavior. Furthermore, the fairness index is defined to assess the effective of the proposed billing mechanism.

The contributions of this dissertation are summarized as follows:

- The proposed DSM model provides utility companies a solution to manage the energy consumption of residential users with DER. Thus, reduce the cost of balancing supply and demand by flattening demand curves.

- The proposed DSM model provides energy end-users the opportunity to increase financial benefits and investment returns for their DER. Thus, exploiting the full value of DER through local energy sharing and DSM.

- The proposed DSM model facilitates the integration of DER toward the decentralization of the future electrical grid. Thus, help reduce global greenhouse gas emission and fight against climate change.

- The proposed rescheduling algorithm and fair billing mechanism improve the practicality of the DSM considering uncertainty from human behavior and schedule deviation.

8.2 Future Work

Although this dissertation fulfills the aim of developing a DSM method to manage energy consumption in a residential community with DERs, there still some works that can be developed in the future. Firstly, we consider battery storage and load shifting as an active DER in this dissertation. Further consideration of other types of DER such as load curtailment and EV could be added to increase flexibility capacity in the demand-side. As a new type of DERs, different scheduling strategies and responses can be invented to further improve the desired system outcomes. Secondly, in the future, the cost of battery storage will decrease and wildly affordable to most of the users. This provides more application for batteries services in the demand-side, e.g., use as a buffer to compensate power fluctuation from intermittent production of renewable energy and prevent deviation of consumption from assigned schedule. Thirdly, the proposed DSM method can be extended to model the interaction and energy sharing among communities (or microgrids). Each community is treated as a single unit and coordinated with the neighboring community in order to trade supply or demand. Due to relatively short distances, utilizing energy close to energy sources would provide more efficient energy usage, less transmission loss, and promoting renewable energy adaptation.

Bibliography

[1] Clean Energy Council. The distributed energy resources revolution: A roadmap for australia's enormous rooftop solar and battery potential. Aug. 2019.

[2] California Independent System Operator. Fast facts: What the duck curve tells us about managing a green grid. 2016.

[3] Eoghan McKenna and Murray Thomson. High-resolution stochastic integrated thermal–electrical domestic demand model. *Applied Energy*, 165:445 – 461, 2016.

[4] Commonwealth Scientific and Industrial Research Organisation. Projections for small scale embedded energy technologies: Report to aemo. Jun. 2019.

[5] Bloomberg Finance L.P. New energy outlook 2019. 2019.

[6] Renewable Energy Institute. Feed-in tariffs in japan: Five years of achievements and future challenges. 2017.

[7] K. Petrou, A. T. Procopiou, L. F. Ochoa, T. Langstaff, and J. Theunissen. Impacts of price-led operation of residential storage on distribution networks: An australian case study. In *2019 IEEE Milan PowerTech*, pages 1–6, June 2019.

[8] A. Mohsenian-Rad, V. W. S. Wong, J. Jatskevich, R. Schober, and A. Leon-Garcia. Autonomous demand-side management based on game-theoretic energy consumption scheduling for the future smart grid. *IEEE Transactions on Smart Grid*, 1(3):320–331, Dec 2010.

[9] US department of energy. The smart grid: An introduction. 2008.

[10] Marc Beaudin and Hamidreza Zareipour. Home energy management systems: A review of modelling and complexity. *Renewable and Sustainable Energy Reviews*, 45:318 – 335, 2015.

[11] US department of energy. Advanced metering infrastructure and customer systems: results from the smart grid investment grant program. Sep. 2016.

[12] Charles River Associates. Primer on demand side management, report for the world bank. Feb. 2005.

[13] US department of energy. Benefits of demand response in electricity markets and recommendations for achieving them. Feb. 2005.

[14] M. H. Albadi and E. F. El-Saadany. Demand response in electricity markets: An overview. In *2007 IEEE Power Engineering Society General Meeting*, pages 1–5, June 2007.

[15] M. O'Sheasy S. Braithwait, D. Hansen. Retail electricity pricing and rate design in evolving markets. *Edison Electric Institute*, Jul. 2007.

[16] Ahmad Faruqui, Ryan Hledik, and John Tsoukalis. The power of dynamic pricing. *The Electricity Journal*, 22(3):42 – 56, 2009.

[17] S. Shao, T. Zhang, M. Pipattanasomporn, and S. Rahman. Impact of tou rates on distribution load shapes in a smart grid with phev penetration. In *IEEE PES T D 2010*, pages 1–6, April 2010.

[18] Ahmad Faruqui, Sanem Sergici, and Ahmed Sharif. The impact of informational feedback on energy consumption—a survey of the experimental evidence. *Energy*, 35(4):1598 – 1608, 2010. Demand Response Resources: the US and International Experience.

[19] Sebastian Gottwalt, Wolfgang Ketter, Carsten Block, John Collins, and Christof Weinhardt. Demand side management—a simulation of household behavior under

variable prices. *Energy Policy*, 39(12):8163 – 8174, 2011. Clean Cooking Fuels and Technologies in Developing Economies.

[20] Karen Herter. Residential implementation of critical-peak pricing of electricity. *Energy Policy*, 35(4):2121 – 2130, 2007.

[21] Guy R. Newsham and Brent G. Bowker. The effect of utility time-varying pricing and load control strategies on residential summer peak electricity use: A review. *Energy Policy*, 38(7):3289 – 3296, 2010. Large-scale wind power in electricity markets with Regular Papers.

[22] Karen Herter and Seth Wayland. Residential response to critical-peak pricing of electricity: California evidence. *Energy*, 35(4):1561 – 1567, 2010. Demand Response Resources: the US and International Experience.

[23] Q. Zhou, W. Guan, and W. Sun. Impact of demand response contracts on load forecasting in a smart grid environment. In *2012 IEEE Power and Energy Society General Meeting*, pages 1–4, July 2012.

[24] W. Chen, X. Wang, J. Petersen, R. Tyagi, and J. Black. Optimal scheduling of demand response events for electric utilities. *IEEE Transactions on Smart Grid*, 4(4):2309–2319, Dec 2013.

[25] E. Bloustein. Assessment of customer response to real time pricing. *Rutgers-The State Univ. New Jersey, Tech. Rep*, 2005.

[26] P. Samadi, A. Mohsenian-Rad, R. Schober, V. W. S. Wong, and J. Jatskevich. Optimal real-time pricing algorithm based on utility maximization for smart grid. In *2010 First IEEE International Conference on Smart Grid Communications*, pages 415–420, Oct 2010.

[27] Z. Chen, L. Wu, and Y. Fu. Real-time price-based demand response management for residential appliances via stochastic optimization and robust optimization. *IEEE Transactions on Smart Grid*, 3(4):1822–1831, Dec 2012.

[28] S. Maharjan, Q. Zhu, Y. Zhang, S. Gjessing, and T. Basar. Dependable demand response management in the smart grid: A stackelberg game approach. *IEEE Transactions on Smart Grid*, 4(1):120–132, March 2013.

[29] J. H. Yoon, R. Baldick, and A. Novoselac. Dynamic demand response controller based on real-time retail price for residential buildings. *IEEE Transactions on Smart Grid*, 5(1):121–129, Jan 2014.

[30] C. Eksin, H. Deliç, and A. Ribeiro. Demand response management in smart grids with heterogeneous consumer preferences. *IEEE Transactions on Smart Grid*, 6(6):3082–3094, Nov 2015.

[31] M. Yu and S. H. Hong. A real-time demand-response algorithm for smart grids: A stackelberg game approach. *IEEE Transactions on Smart Grid*, 7(2):879–888, March 2016.

[32] P. Jacquot, O. Beaude, S. Gaubert, and N. Oudjane. Analysis and implementation of an hourly billing mechanism for demand response management. *IEEE Transactions on Smart Grid*, 10(4):4265–4278, July 2019.

[33] Smart Energy Demand Coalition. Mapping demand response in europe today. Sep. 2015.

[34] F. Rahimi and A. Ipakchi. Demand response as a market resource under the smart grid paradigm. *IEEE Transactions on Smart Grid*, 1(1):82–88, June 2010.

[35] N. Li, L. Chen, and S. H. Low. Optimal demand response based on utility maximization in power networks. In *2011 IEEE Power and Energy Society General Meeting*, pages 1–8, July 2011.

[36] S. Datchanamoorthy, S. Kumar, Y. Ozturk, and G. Lee. Optimal time-of-use pricing for residential load control. In *2011 IEEE International Conference on Smart Grid Communications (SmartGridComm)*, pages 375–380, Oct 2011.

[37] I. Atzeni, L. G. Ordóñez, G. Scutari, D. P. Palomar, and J. R. Fonollosa. Demand-side management via distributed energy generation and storage optimization. *IEEE Transactions on Smart Grid*, 4(2):866–876, June 2013.

[38] Z. Wang, C. Gu, F. Li, P. Bale, and H. Sun. Active demand response using shared energy storage for household energy management. *IEEE Transactions on Smart Grid*, 4(4):1888–1897, Dec 2013.

[39] H. M. Soliman and A. Leon-Garcia. Game-theoretic demand-side management with storage devices for the future smart grid. *IEEE Transactions on Smart Grid*, 5(3):1475–1485, May 2014.

[40] Wayes Tushar, Jian A. Zhang, David B. Smith, H. Vincent Poor, and Sylvie Thiébaux. Prioritizing consumers in smart grid: A game theoretic approach. *IEEE Transactions on Smart Grid*, 5(3):1429–1438, 2014.

[41] H. K. Nguyen, J. B. Song, and Z. Han. Distributed demand side management with energy storage in smart grid. *IEEE Transactions on Parallel and Distributed Systems*, 26(12):3346–3357, Dec 2015.

[42] N. Forouzandehmehr, M. Esmalifalak, H. Mohsenian-Rad, and Z. Han. Autonomous demand response using stochastic differential games. *IEEE Transactions on Smart Grid*, 6(1):291–300, Jan 2015.

[43] N. G. Paterakis, O. Erdinç, A. G. Bakirtzis, and J. P. S. Catalão. Optimal household appliances scheduling under day-ahead pricing and load-shaping demand response strategies. *IEEE Transactions on Industrial Informatics*, 11(6):1509–1519, Dec 2015.

[44] Milad Latifi, Azam Khalili, Amir Rastegarnia, Sajad Zandi, and Wael M. Bazzi. A distributed algorithm for demand-side management: Selling back to the grid. *Heliyon*, 3(11):e00457, 2017.

[45] L. Jiang and S. Low. Real-time demand response with uncertain renewable energy in smart grid. In *2011 49th Annual Allerton Conference on Communication, Control, and Computing (Allerton)*, pages 1334–1341, Sep. 2011.

[46] S. Maharjan, Y. Zhang, S. Gjessing, and D. H. K. Tsang. User-centric demand response management in the smart grid with multiple providers. *IEEE Transactions on Emerging Topics in Computing*, 5(4):494–505, Oct 2017.

[47] E. Hooshmand and A. Rabiee. Robust model for optimal allocation of renewable energy sources, energy storage systems and demand response in distribution systems via information gap decision theory. *IET Generation, Transmission Distribution*, 13(4):511–520, 2019.

[48] X. Yang, Y. Zhang, H. He, S. Ren, and G. Weng. Real-time demand side management for a microgrid considering uncertainties. *IEEE Transactions on Smart Grid*, 10(3):3401–3414, May 2019.

[49] S. K. Vuppala, K. Padmanabh, Sumit Kumar Bose, and S. Paul. Incorporating fairness within demand response programs in smart grid. In *ISGT 2011*, pages 1–9, Jan 2011.

[50] Z. Baharlouei, H. Narimani, and H. Mohsenian-Rad. Tackling co-existence and fairness challenges in autonomous demand side management. In *2012 IEEE Global Communications Conference (GLOBECOM)*, pages 3159–3164, Dec 2012.

[51] Z. Baharlouei, M. Hashemi, H. Narimani, and H. Mohsenian-Rad. Achieving optimality and fairness in autonomous demand response: Benchmarks and billing mechanisms. *IEEE Transactions on Smart Grid*, 4(2):968–975, June 2013.

[52] Z. Baharlouei and M. Hashemi. Efficiency-fairness trade-off in privacy-preserving autonomous demand side management. *IEEE Transactions on Smart Grid*, 5(2):799–808, March 2014.

[53] E. Pournaras, M. Vasirani, R. E. Kooij, and K. Aberer. Measuring and controlling unfairness in decentralized planning of energy demand. In *2014 IEEE International Energy Conference (ENERGYCON)*, pages 1255–1262, May 2014.

[54] G. O'Brien, A. El Gamal, and R. Rajagopal. Shapley value estimation for compensation of participants in demand response programs. *IEEE Transactions on Smart Grid*, 6(6):2837–2844, Nov 2015.

[55] N. Yaagoubi and H. T. Mouftah. Fairness-aware game theoretic approach for demand response in microgrids. In *2015 Seventh Annual IEEE Green Technologies Conference*, pages 125–131, April 2015.

[56] S. Bakr and S. Cranefield. Using the shapley value for fair consumer compensation in energy demand response programs: Comparing algorithms. In *2015 IEEE International Conference on Data Science and Data Intensive Systems*, pages 440–447, Dec 2015.

[57] M. Ghorbanian, H. Narimani, and G. R. Yousefi. Billing mechanism design in an autonomous demand side management in a smart distribution network. In *2017 Iranian Conference on Electrical Engineering (ICEE)*, pages 1284–1290, May 2017.

[58] P. Jacquot, O. Beaude, S. Gaubert, and N. Oudjane. Demand side management in the smart grid: An efficiency and fairness tradeoff. In *2017 IEEE PES Innovative Smart Grid Technologies Conference Europe (ISGT-Europe)*, pages 1–6, Sep. 2017.

[59] T. Assaf, A. H. Osman, and M. Hassan. Fair autonomous energy consumption scheduling based on game-theoretic approach for the future smart grid. In *2016 UKSim-AMSS 18th International Conference on Computer Modelling and Simulation (UKSim)*, pages 235–239, April 2016.

[60] T. Assaf, A. H. Osman, M. S. Hassan, and H. Mir. Fair and efficient energy consumption scheduling algorithm using tabu search for future smart grids. *IET Generation, Transmission Distribution*, 12(3):643–649, 2018.

[61] M. Khorasany, Y. Mishra, and G. Ledwich. Market framework for local energy trading: a review of potential designs and market clearing approaches. *IET Generation, Transmission Distribution*, 12(22):5899–5908, 2018.

[62] PricewaterhouseCoopers. Blockchain – an opportunity for energy producers and consumers? 2016.

[63] K. Christidis and M. Devetsikiotis. Blockchains and smart contracts for the internet of things. *IEEE Access*, 4:2292–2303, 2016.

[64] M. Andoni, V. Robu, and D. Flynn. Crypto-control your own energy supply. *Nature*, 548(158), Aug 2017.

[65] Tiago Sousa, Tiago Soares, Pierre Pinson, Fabio Moret, Thomas Baroche, and Etienne Sorin. Peer-to-peer and community-based markets: A comprehensive review. *Renewable and Sustainable Energy Reviews*, 104:367 – 378, 2019.

[66] P. Samadi, V. W. S. Wong, and R. Schober. Load scheduling and power trading in systems with high penetration of renewable energy resources. *IEEE Transactions on Smart Grid*, 7(4):1802–1812, July 2016.

[67] N. Liu, X. Yu, C. Wang, C. Li, L. Ma, and J. Lei. Energy-sharing model with price-based demand response for microgrids of peer-to-peer prosumers. *IEEE Transactions on Power Systems*, 32(5):3569–3583, Sep. 2017.

[68] N. Liu, X. Yu, C. Wang, and J. Wang. Energy sharing management for microgrids with pv prosumers: A stackelberg game approach. *IEEE Transactions on Industrial Informatics*, 13(3):1088–1098, June 2017.

[69] W. Tushar, C. Yuen, D. B. Smith, and H. V. Poor. Price discrimination for energy trading in smart grid: A game theoretic approach. *IEEE Transactions on Smart Grid*, 8(4):1790–1801, July 2017.

[70] F. Moret and P. Pinson. Energy collectives: a community and fairness based approach to future electricity markets. *IEEE Transactions on Power Systems*, pages 1–1, 2018.

[71] Chao Long, Jianzhong Wu, Yue Zhou, and Nick Jenkins. Peer-to-peer energy sharing through a two-stage aggregated battery control in a community microgrid. *Applied Energy*, 226:261 – 276, 2018.

[72] W. Tushar, T. K. Saha, C. Yuen, P. Liddell, R. Bean, and H. V. Poor. Peer-to-peer energy trading with sustainable user participation: A game theoretic approach. *IEEE Access*, 6:62932–62943, 2018.

[73] Alexandra Lüth, Jan Martin Zepter, Pedro Crespo del Granado, and Ruud Egging. Local electricity market designs for peer-to-peer trading: The role of battery flexibility. *Applied Energy*, 229:1233 – 1243, 2018.

[74] Yue Zhou, Jianzhong Wu, and Chao Long. Evaluation of peer-to-peer energy sharing mechanisms based on a multiagent simulation framework. *Applied Energy*, 222:993 – 1022, 2018.

[75] Jan Martin Zepter, Alexandra Lüth, Pedro Crespo del Granado, and Ruud Egging. Prosumer integration in wholesale electricity markets: Synergies of peer-to-peer trade and residential storage. *Energy and Buildings*, 184:163 – 176, 2019.

[76] T. Morstyn and M. D. McCulloch. Multiclass energy management for peer-to-peer energy trading driven by prosumer preferences. *IEEE Transactions on Power Systems*, 34(5):4005–4014, Sep. 2019.

[77] A. Paudel, K. Chaudhari, C. Long, and H. B. Gooi. Peer-to-peer energy trading in a prosumer-based community microgrid: A game-theoretic model. *IEEE Transactions on Industrial Electronics*, 66(8):6087–6097, Aug 2019.

[78] J. Guerrero, A. C. Chapman, and G. Verbič. Decentralized p2p energy trading under network constraints in a low-voltage network. *IEEE Transactions on Smart Grid*, 10(5):5163–5173, Sep. 2019.

[79] J. L. Mathieu, M. G. Vayá, and G. Andersson. Uncertainty in the flexibility of aggregations of demand response resources. In *IECON 2013 - 39th Annual Conference of the IEEE Industrial Electronics Society*, pages 8052–8057, Nov 2013.

[80] Toby Couture and Yves Gagnon. An analysis of feed-in tariff remuneration models: Implications for renewable energy investment. *Energy Policy*, 38(2):955 – 965, 2010.

[81] Xavier Vives. Strategic supply function competition with private information. *Econometrica*, 79(6):1919–1966, 2011.

[82] Esther Mengelkamp, Johannes Gärttner, Kerstin Rock, Scott Kessler, Lawrence Orsini, and Christof Weinhardt. Designing microgrid energy markets: A case study: The brooklyn microgrid. *Applied Energy*, 210:870 – 880, 2018.

[83] sonnen GmbH. Technical data sonnenbatterie eco 8.0, 2018. 2018.

[84] Tokyo Electric Power Company. Electricity rate plans. 2019.

[85] U.S. Department of Energy. Gridlab-d. 2019.

[86] R. Deng, Z. Yang, J. Chen, N. R. Asr, and M. Chow. Residential energy consumption scheduling: A coupled-constraint game approach. *IEEE Transactions on Smart Grid*, 5(3):1340–1350, May 2014.

[87] L. Yang, X. Chen, J. Zhang, and H. V. Poor. Cost-effective and privacy-preserving energy management for smart meters. *IEEE Transactions on Smart Grid*, 6(1):486–495, Jan 2015.

[88] N. Good, E. Karangelos, A. Navarro-Espinosa, and P. Mancarella. Optimization under uncertainty of thermal storage-based flexible demand response with quantification of residential users' discomfort. *IEEE Transactions on Smart Grid*, 6(5):2333–2342, Sep. 2015.

[89] K. Petrou, L. F. Ochoa, A. T. Procopiou, J. Theunissen, J. Bridge, T. Langstaff, and K. Lintern. Limitations of residential storage in pv-rich distribution networks:

An australian case study. In *2018 IEEE Power Energy Society General Meeting (PESGM)*, pages 1–5, Aug 2018.

[90] A. I. Negash, T. W. Haring, and D. S. Kirschen. Allocating the cost of demand response compensation in wholesale energy markets. *IEEE Transactions on Power Systems*, 30(3):1528–1535, 2015.

Publications

Journals

[1] P. Charoen, S. Javaid, M. Sioutis, Y. Lim and Y. Tan, “Dynamic Pricing with Local Energy Sharing in Demand-Side Management,” *IEEE Transactions on Smart Grid.* (**Submitted, Under Review**)

[2] P. Charoen, M. Sioutis, S. Javaid, C. Charoenlarpnopparut, Y. Lim, and Y. Tan, “User-Centric Consumption Scheduling and Fair Billing Mechanism in Demand-Side Management,” *Energies*, vol.12, no.1, pp. 156, 2019.

International Conference

[3] P. Charoen, S. Javaid, M. Sioutis, Y. Lim and Y. Tan, ”Demand-Side Management with Local Energy Sharing Model for Prosumer Communities,” *9th International Conference on Power and Energy System (ICPES)*, Perth, Australia, 2019. (Accepted for publication)

[4] P. Charoen, M. Sioutis, S. Javaid, Y. Lim and Y. Tan, ”Fair Billing Mechanism for Energy Consumption Scheduling with User Deviation in the Smart Grid,” *6th International Conference on Smart Energy Grid Engineering (SEGE)*, ON, Canada, 2018, pp. 84-88.

[5] P. Charoen, S. Javaid, Y. Lim, Y. Tan and C. Charoenlarpnopparut, ”Adaptive Rescheduling of Energy Consumption Based on User Preferences for the Future

Smart Grid," *IEEE PES Innovative Smart Grid Technologies - Asia (ISGT-Asia)*, Singapore, 2018, pp. 36-41.

Domestic Conferences

[6] P. Charoen, S. Javaid, Y. Lim and Y. Tan, "Demand side management for the future smart grid," *JAIST World Conference (JWC)*, Ishikawa, Japan, 2018.

Appendices

Appendix A: Local energy price functions

We use the inverse-proportional relationship between price and SDR, $1/(ax + b)$, as a fitting function to formulate the local selling price function as follows

$$p_{l,s} = \frac{1}{a \cdot SDR + b}. \tag{8.1}$$

We also consider the following points,

- When SDR = 0, a local selling price ($p_{l,s}$) should equal to a price that the CEC purchase energy from the utility company ($p_{g,b}$) since no local supply is available and all the demand need to be fulfilled from the grid.
- When SDR $\geq$ 1, a local selling price ($p_{l,s}$) should equal to a price that the CEC sold energy to the utility company ($p_{g,s}$) since the excess PV energy must export back to the grid according to the FIT program.

Hence, we can obtain the following equations:

$$\frac{1}{a \cdot (0) + b} = p_{g,b} \tag{8.2}$$

and

$$\frac{1}{a \cdot (1) + b} = p_{g,s} \tag{8.3}$$

Solving for a and b, we get

$$a = \frac{p_{g,b} - p_{g,s}}{p_{g,b}p_{g,s}} \tag{8.4}$$

and

$$b = \frac{1}{p_{g,b}} \tag{8.5}$$

By substitute a and b into (8.1), the local selling price function can be formulated as

$$p^h_{l,s} = \begin{cases} \frac{p^h_{g,s}p^h_{g,b}}{(p^h_{g,b}-p^h_{g,s})SDR^h+p^h_{g,s}} & ,0 \leq SDR^h \leq 1 \\ p^h_{g,s} & ,SDR^h > 1. \end{cases} \tag{8.6}$$

For the local buying price function, we first assume that the CEC also employ *a budget balanced* scheme, e.g., total revenue is equal to total expense, as in the following expression

$$E_b \cdot p_{l,b} = |E_s| \cdot p_{l,s} + (E_b - |E_s|) \cdot p_{g,b}. \tag{8.7}$$

By substituting $|E_s| = E_b \cdot SDR$, we get

$$p_{l,b} = p_{l,s} \cdot SDR + (1 - SDR) \cdot p_{g,b}. \tag{8.8}$$

When SDR ≥ 1, the local buying price also equal to the FIT similar to the condition of the local selling price. Thus, the local buying price function can be formulated as

$$p^h_{l,b} = \begin{cases} p^h_{l,s}SDR^h + (1 - SDR^h)p^h_{g,b} & ,0 \leq SDR^h \leq 1 \\ p^h_{g,s} & ,SDR^h > 1. \end{cases} \tag{8.9}$$

Appendix B: Household appliance list

The list of appliance and type are shown in Table 8.1. The full detail of appliance specification can be referred in [3]. Note that the classification of activities as flexible or non-flexible may be perceived as arbitrary. However, by applying different user preferences, an activity can be effectively reclassified as to fulfill the user's needs.

Table 8.1: List of appliances.

Appliance	**Type**
Cassette/CD player	Non-flexible
Chest freezer	Non-flexible
Dish washer	Flexible
Domestic electric storage water heater	Flexible
Electric instantaneous water heater	Flexible
Electric shower	Flexible
Electric space heating	Non-flexible
Fax	Non-flexible
Fridge freezer	Non-flexible
Hi-Fi	Non-flexible
Hob	Flexible
Iron	Flexible
Kettle	Flexible
Lighting	Non-flexible
Microwave	Flexible
Oven	Flexible
Personal computer	Non-flexible
Printer	Non-flexible
Refrigerator	Non-flexible
Small cooking group	Flexible
Storage heaters	Non-flexible
Tumble dryer	Flexible
TV 1	Non-flexible
TV 2	Non-flexible
TV 3	Non-flexible
TV receiver box	Non-flexible
Upright freezer	Non-flexible
Vacuum	Flexible
VCR/DVD	Non-flexible
Washer dryer	Flexible
Washing machine	Flexible