AUTONOMOUS DEMAND-SIDE MANAGEMENT IN THE FUTURE SMART GRID

by

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Approval Signatures

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Dedication . . . To my family

Abstract

Group Autonomous Demand-Side Management (ADSM) programs provide practical mechanisms to coordinate energy consumption to achieve smart grid-wide objectives, such as reducing the energy cost, reducing the Peak-to-Average Ratio (PAR), and increasing the penetration of Renewable Energy Sources (RESs). In this work, a group ADSM program, where the customers cooperate to reduce their energy cost payment through scheduling the future energy consumption profiles, is investigated. First, an aggregative game is formulated to model the strategic behavior of the customers. Subsequently, in order to consider the computational complexity and limitations of the group ADSM programs, an efficient energy consumption scheduling algorithm based on Tabu Search (TS) is proposed. In addition to the ability of achieving the near-optimal energy schedules, the computational time is reduced to a large extent as compared to the energy scheduling algorithm based on Parallel Monte Carlo Tree Search (P-MCTS) and the benchmark energy scheduling algorithm based on Branch and Bound (BB). Moreover, a billing mechanism that charges customers fairly based on their energy consumption and commitment to abide by the assigned schedules and program rules is developed. Two systems are considered; Single-Source Multiple-Customers (SSMC) system and Multiple-Sources Multiple-Customers (MSMC) system. In the SSMC system, a central energy source is shared among customers, while the MSMC system consists of a central energy source, distributed RESs, and Distributed Storage Elements (DSEs). Simulation results confirm that the proposed billing mechanism enhances the fairness level of the system and the proposed algorithm ensures a considerable reduction in the computational complexity. In addition, due to the utilization of distributed RESs and DSEs in the MSMC system, both the level of greenhouse emissions and the total system cost are guaranteed to be reduced compared to the SSMC system.

Search Terms: ***smart grid, autonomous demand-side management, renewable energy sources, microgrid, computational complexity, fairness, game theory, Tabu search.***

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Chapter 1: Introduction

Electricity is the lifeline of civilization and the most fundamental infrastructure of modern society and economy. Most of the world relies on the traditional electricity grid operations that have not changed much since the 1930s and their supporting data communications which resemble the means introduced in 1970s. As a result, the growth in transmission capacity lags far behind the growth in generation and load which increasingly stresses the grid. This raises an imminent and urgent need to shift towards a more efficient, reliable and greener energy system to respond to today's ever-changing demand and emerging global challenges. The smart grid will be a necessary enabler of this transition which is an interconnected power network of transmission, distribution, communications, controls, and advanced technologies working together to match customers' needs [1].

The evolution of smart grid technologies will allow customers to make more informed decisions about their energy consumption, adjusting both the timing and quantity of their electricity use. This ability to control usage is called Demand-Side Management (DSM). The DSM offers the promise of cutting costs for commercial customers, saving money for households, and helping utilities operate more efficiently and reliably, in turn lowering the need to build new expensive generation plants and reducing emissions of greenhouse gases. The DSM is a set of interconnected and flexible programs which allows customers a greater role in shifting their own load for electricity during peak periods, reducing their energy consumption cost and Peak-to-Average Ratio (PAR), and increasing the penetration of Renewable Energy Sources (RESs) [1].

Issues such as: large control overhead on utilities, difficultly of manually responding to hourly changing prices by customers, and load synchronization are the main challenges when implementing DSM programs. As an alternative, Autonomous DSM (ADSM) programs have been recently proposed. The key idea is in equipping each customer's smart meter with an Energy Consumption Scheduling (ECS) capability to automatically manage the load consumption based on smart pricing paradigm [2]. ADSM programs can be divided into two categories: individual ADSM and group ADSM. In the individual ADSM programs, each customer interacts directly with the utility to individually reduce the electricity payment or reduce the load profile PAR. On the other hand, in the group ADSM programs, a group of customers coordinate their energy consumption such that the total system cost and the system PAR are reduced. Group ADSM is the main focus of this work.

An important and nontrivial engineering issue is the integration of RESs, such as wind, water, and the sun, into the smart grid. These sources of power are typically subject to the vagaries of environmental conditions, which introduce significant variability and instability in supply. Group ADSM programs can significantly mitigate the impact of RESs variability through encouraging customers to adapt certain consumption patterns which increase the penetration of such sources. In addition, these programs can efficiently utilize the two-way information and power exchange networks, supported by the grid, which enable consumers to not only draw power but supply surplus power to the grid as well.

In most of the literature works, the group ADSM programs are successful in achieving the grid-wide objectives, such as reducing the total energy cost, reducing the PAR, etc. However, most of these works ignore that in reality, the success of group ADSM programs relies on the active participation and satisfaction of customers. A variety of incentives can be offered by the grid to motivate customers to participate in such programs. The monetary incentives are among the most common ones by which customers are encouraged to follow a certain electricity load pattern in order to achieve the lowest possible bill payment. However, it is shown in [3, 4] that the financial incentives cannot fully capture the interest of customers to these programs.

In this work, a fair and efficient group ADSM program for the scheduling of a day-ahead energy consumption in the residential sector, is proposed. Two systems are considered; Single-Source Multiple-Customers (SSMC) system and Multiple-Sources Multiple-Customers (MSMC) system. In the SSMC system, only a central energy source (e.g., a generator or a step-down substation transformer) is shared among customers, while the MSMC system consists of a central energy source, distributed RESs (rooftop Photovoltaic (PV) panels), and DSEs (e.g., batteries). The main incentives that motivate customers to participate in the proposed program are reducing electricity payment, assuring fairness, increasing the computational efficiency, and increasing the penetration of RESs while maintaining the balance between demand and supply. Numerical and simulation results for several case studies are provided to demonstrate the effectiveness of the proposed work.

1.1. Problem Statement

Recently, group ADSM has emerged as one of the key mechanisms that make the smart grid more efficient, reliable, and cost-effective. Dynamic pricing has been regarded as a promising mechanism towards a successful implementation of group ADSM due to its ability in motivating customers to reduce their peak load and reshape the pattern of their energy use. However, the financial incentives are not enough and the success of group ADSM programs considerably depends on customers' level of involvement and contribution. Several incentives could be provided to encourage customers to participate in group ADSM programs. In this thesis, incentive-based group ADSM programs for the smart grid in the residential sector are proposed. Devising a fair billing mechanism which penalizes customers who do not abide by the assigned energy consumption schedules, implementing an efficient energy consumption scheduling based on Tabu Search (TS) algorithm, reducing the total system cost, and increasing the penetration of RESs are the incentives applied in this work.

1.2. Thesis Objectives

The main objectives of this work are as follows.

1. Develop a group ADSM program based on a game-theoretic approach for a day-ahead energy consumption scheduling for residential customers in the SSMC system to reduce the total system cost.
2. Develop a group ADSM program based on a game-theoretic and a Deterministic Energy Management (DEM) approaches for a day-ahead energy consumption scheduling for residential customers in the MSMC system to reduce the total system cost, and increase the penetration of RESs.
3. Develop an efficient energy consumption scheduling algorithm based on TS in the SSMC and MSMC systems.

4. Develop a fair billing mechanism that penalizes customers who violate the assigned, and near-optimal energy schedules in the SSMC and MSMC systems.

1.3. Thesis Contributions

The major contributions of this thesis are explained as follows.

- A new energy consumption billing mechanism that takes into account the impact of customers' violations on the SSMC and MSMC systems performance and how to deal with it to ensure a higher level of fairness, is proposed.
- A new energy consumption scheduling strategy for the MSMC system to tackle the intermittency nature of solar energy generation through the implementation of DEM strategy combined with an aggregative game, is proposed.
- A day-ahead energy consumption scheduling algorithm based on TS for an efficient implementation of group ADSM programs in the SSMC and MSMC systems, is applied. The proposed algorithm is compared in terms of results accuracy and computational time with the benchmark Branch and Bound (BB) search and the Parallel-Monte Carlo Tree Search (P-MCTS) methods.

1.4. Thesis Outline

This thesis is organized as follows. Chapter 1 presents an introduction to the research field, the objectives, and the main contributions of this thesis. The background to this research topic as well as the latest advances and the progress achieved so far, are presented in Chapter 2. In Chapter 3, the group ADSM progam in the SSMC system is explained. The group ADSM program in the MSMC system is presented in Chapter 4. Finally, Chapter 5 outlines the conclusion and the future work.

Chapter 2: Demand-Side Management (DSM)

The concept of DSM can be traced back to the 1970's in response to the energy crisis in the United States [5]. The power of DSM lies in eliminating resource bottlenecks, integrating RESs, reducing peaky demand profiles, and engaging customers in supply-demand issues. One of the widely accepted and descriptive definitions for DSM is provided by Gellings as: "Demand-Side Management is the planning and implementation of those utility activities designed to influence customer use of electricity in ways that will produce desired changes in the utility's load shape, i.e., in the time pattern and the magnitude of a utility's load" [6].

DSM covers all the management aspects associated with demand-side activities such as planning, evaluation, implementation, and monitoring. Moreover, DSM can be applied to residential, commercial, and industrial sectors.

2.1. Demand-Side Management (DSM) Types

DSM types generally fall into three main categories: Load management (LM), Demand response (DR), and Energy efficiency (EE).

2.1.1. Load management (LM). LM is a power utility strategy that is developed for matching demand with supply by influencing the timing and magnitude of a customer's electricity consumption [6]. The traditional LM falls into fours schemes: peak clipping, valley filling, load shifting, and strategic conservation. Peak clipping is a classic scheme that aims at reducing the peak load at specific time slots by means of direct control. Valley filling scheme aims at building up off-peak loads when the long-term average price is lower than the cost of load building in the off-peak hours. Furthermore, load shifting technique simply shifts the electricity load from peak hours to off-peak hours. Finally, strategic conservation is the change in the load profile that occurs from utility-driven conservation activities such as turning up the air conditioner thermostat at a few degrees in summer [7]. The concepts of the four schemes are illustrated in Fig. 1.

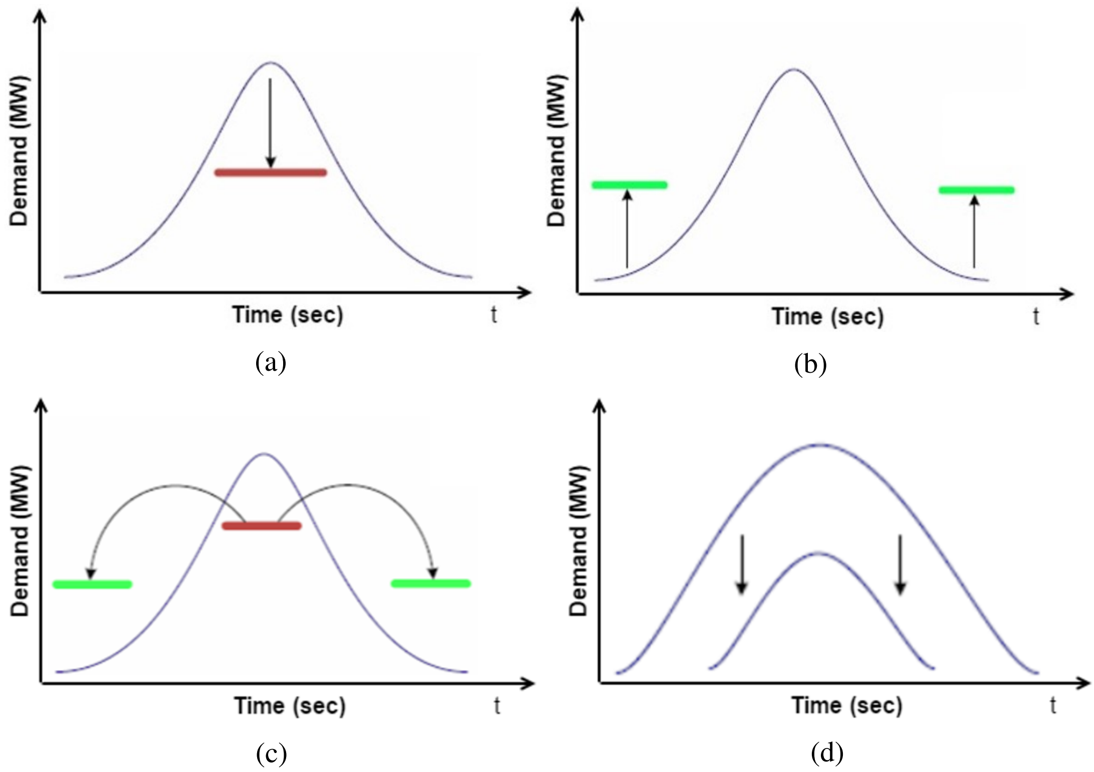


Figure 1: (a) Peak clipping (b) Valley filling (c) Load shifting (d) Strategic conversion [1].

2.1.2. Demand response (DR). In principle, DR is defined as time-dependent programs that motivate customers to change their daily electricity consumption profiles in response to changes in the price of electricity. In addition, DR is featured by the incentive payments provided to customers to induce lower electricity consumption at times when system reliability and stability are jeopardized. DR includes all dynamic and event-driven electricity consumption pattern strategies performed by customers. These strategies are intended to respond to the wholesale market changes by altering the timing, level of instantaneous load, or total electricity consumption. DR programs are divided into Incentive-Based Program (IBP) and Time-Based Program (TBP) [8].

The IBP category is classified into classical programs and market based programs. The classical programs are further divided into Direct Load Control (DLC) and Interruptible/Curtailable Service (I/C). In DLC programs, utility operators have the ability to remotely shut down customers' appliances on short notice in exchange for an incentive payment. On the other hand, customers on I/C service receive rate discount or bill credit in exchange for voluntarily reducing their load to predefined values by the utility. The market based programs are divided into several subgroups: load bidding, emergency DR, capacity market, and ancillary service market.

To start with, load bidding programs encourage customers to bid on load reductions with a price at which they are intended to be curtailed. A bid is approved by the utility if it is cheaper than the market price of alternative supply bids. Generally, load bidding is attractive to customers as they enable them to keep a fixed rate and receive higher payments for the load reduction bids when the market prices are high. Emergency DR program is another type of the market based categories where customers are paid incentives for reducing their load during reliability-triggered events or emergency conditions, but curtailment is optional [8]. In capacity market programs, customers commit to providing prespecified load reductions when system contingencies arise, and they face penalties if they do not respond to calls for load curtailment [9]. Finally, ancillary service market programs provide customers with the choice to bid on load curtailments as in the operating reserve markets. If the bids are accepted, customers are paid the market price for committing to be on standby, and if load reduction is required they are paid the spot market electricity price [8, 10].

The second type of DR programs is the TBP which relies on dynamic pricing rates that reflect the true market price for electricity generation and distribution. At first, these programs are intended to flatten the load profile through offering high prices at peak hours and lower prices at off-peak hours. There are different pricing mechanisms under the umbrella of TBP: Time of Use (ToU), Critical Peak Pricing (CPP), Extreme Day CPP (ED-CPP), Extreme Day Pricing (EDP), and Real-Time Pricing (RTP).

ToU is a static pricing technique which reflects long-term electricity system cost. In order to reduce the complexity of this technique, the day is divided into two pricing periods, namely peak and off-peak hours, and the pricing rate is defined as the electricity price per unit consumption that varies in each block [11, 12]. Regarding CPP, in essence, it is a form of ToU programs that rewards customers for reducing or shifting their electricity usage voluntarily. However, unlike ToU, CPP limits the peak times to a few times during the year when load is expected to be highest [11]. In ED-CPP programs, responsive customers are rewarded for reducing or shifting their loads during extreme days [12]. On the other hand, EDP has the same concept of CPP in having higher pricing rates of electricity at peak times; however, the rates are in effect for the whole 24 hours of the extreme day [13]. The widely common used TBP program is the RTP which is an hourly fluctuating price of electricity during the day based on real-time information such as wholesale market prices, utility's load electricity, etc. Customers can buy their power for the best available price and savings can be substantial.

2.1.2.1. Energy efficiency (EE). Finally, the EE activity reduces load consumption while offering the same level of electricity service to customers. Actually, EE programs provide incentives to customers who use appliances that consume energy more efficiently. By adopting EE programs, peak load can be permanently lowered, hence reduce the overall load. However, such programs are not as widely used as other DSM programs due to the inconvenience caused to customers as their total energy consumption is reduced. As most of the DR techniques, new technologies and infrastructure are required such as energy efficient appliances and enhanced communications topologies between the customers and utilities [10].

2.2. Demand-Side Management (DSM) Challenges

There are several challenges and issues associated with DSM implementation and development. The main challenges are as follows [14].

- Lack of information, communication, and technology infrastructure.
- Lack of educational and awareness programs about DSM, its functionality and benefits.
- DSM solutions generally add more complexity to the system operations compared with the traditional network solutions.
- Lack of incentives provided to customers in DSM programs.
- Constructing appropriate infrastructure and distribution systems are very expensive.
- The monopoly in the current electricity market.

2.3. Demand-Side Management (DSM) in the Smart Grid

The smart grid introduces a two-way dialogue where electricity and information can be exchanged between the utility and its customers. It is a developing network of communications, controls, automation, and new technologies and tools working together to make the grid more efficient, more reliable, more secure, and greener. The smart grid enables newer technologies to be integrated, such as wind and solar energy production, and plug-in electric vehicles. The grid is expected to replace the aging infrastructure of today's grid to enable customers and operators to better communicate their needs.

As stated by [6], the smart grid vision includes the following aspects:

1. Providing two-way flow of power and information technologies to create an automated energy distribution network.
2. Constructing Information and Communication Technology (ICT) infrastructure to deliver real-time information and achieve the balance between demand and supply.
3. Providing customers with a common pricing model. This model is required for all forms of dynamic pricing and DSM programs.

The smart grid vision brings new challenges and opportunities for DSM. The construction of a new ICT infrastructure in the smart grid is a valuable opportunity to improve the performance and feasibility of DSM programs. In addition, the intelligent appliances, dynamic pricing, and other smart grid technologies facilitate the automation of the DSM process.

The smart grid supports the integration of RESs and storage elements that may raise some challenges to the implementation of DSM. The intermittency of RESs will jeopardize the efficiency of DSM programs, unless, advanced dynamic, interactive pricing mechanisms, accurate prediction methods, efficient computational techniques, etc, are utilized.

The implementation of the smart grid and the DSM programs require advanced communication and power infrastructures to optimize the energy consumption. However, such advancements may take a long time, require huge budgets, and need extensive efforts by economists and researchers to be realized.

2.4. Demand-Side Management (DSM) and Game Theory in the Smart Grid

Game theory can be defined as an analytical framework which enables the study of complex interactions among independent rational players using a set of mathematical tools. Game theory was pioneered in the 1950s by the mathematician John Nash. Game theory has incredibly been adopted in several disciplines such as economics, politics, biology, psychology, and military [15].

Game theory framework can be divided into two main branches: noncooperative game theory and cooperative game theory. Noncooperative game theory can be used to analyze the strategic decision-making processes of a group of independent players, who have conflicting interests over the outcome of a decision process. Mainly, noncooperative games can be seen as capturing a distributed decision-making process that allows the players to optimize, without any coordination or communication, objective functions. On the other side, cooperative game can be used to analyze the strategic decision-making processes of a number of independent players, that have agreed to work together toward a common goal [16].

Game theory is expected to constitute as an essential analytical tool in the design of the future smart grid. The proposed advanced technologies and services in the smart grid systems imply that tools such as game theory will naturally become a prominent tool in the design and analysis of smart grids. In particular, there is a need to deploy models that can capture the need for distributed operation of the smart grid nodes for communication and control purposes and the heterogeneous nature of the smart grid which is typically composed of a variety of nodes such as microgrids, smart meters, appliances, and others [1].

One of the key challenges of the future smart grid is designing DSM models that enable efficient management of the power supply and demand. DSM schemes will always face technical challenges such as pricing, regulations, adaptive decision-making, users' interactions, and dynamic operation. All of these issues are cornerstones to game theory, and, hence, this area is ripe for game theoretic techniques. In fact, DSM is perhaps the most natural setting for applying game theory due to the need of combining economical aspects such as pricing with strategic decision-making by the various involved entities such as the suppliers and the consumers [15].

2.5. Tabu Search (TS)

In this work, TS is utilized as a computationally efficient algorithm to implement the proposed group ADSM programs in the future smart grid. TS was created by Fred Glover in 1986 and formulated in 1989 [17]. TS is a meta-heuristic algorithm that can be used for solving combinatorial optimization problems. Current applications of TS span over the areas of resources planning, telecommunications, VLSI design, financial analysis, energy distribution, molecular engineering, waste management, mineral exploration, biomechanical analysis, environmental conservation and many others. TS is often benchmarked against other meta-heuristic methods such as simulated annealing, genetic algorithms, and colony optimization algorithms [18].

TS employs the concept of local search methods, which are used for mathematical optimization. Generally, the local search methods have a tendency to get stuck in suboptimal regions or on plateaus where many solutions are equally fit. TS enhances the performance of local searches by relaxing their basic rule. First, at each step, worsening moves can be accepted if no improving move is available. In addition, prohibitions are introduced to discourage the search from coming back to previously visited solutions. The implementation of TS uses memory structures that describe the visited solutions or use provided sets of rules. If a potential solution has been previously visited within a certain short-term period or if it has violated a rule, then it is considered as a "Tabu". As a result, the algorithm does not consider that possibility repeatedly. The word "Tabu" comes from the Tongan language of Polynesia used to indicate things that cannot be touched. By the utilization of these memory structures, the search progresses by iteratively moving from the current solution to an improved solution. These memory structures form what is known as the Tabu list, which is a set of rules and band solutions used to filter which solutions will be admitted to the neighborhood to be explored by the search. In its simplest form, a Tabu list is a short-term set of solutions that have been visited in the recent past. The memory structures used in research can be roughly divided into three categories. First, short-term memory is recently considered if a potential solution appears on the Tabu list. The solution cannot be revisited until it reaches an expiration point. Second, intermediate-term memory, which is a set of intensification rules intended to bias the search towards promising areas of the search space. Third, long-term memory, which is a set of diversification rules that drive the search into new regions. Actually, the three structures can overlap in practice [17].

2.6. Literature Review

A wide range of DSM programs has been investigated in the literature. Traditionally, DSM programs were mostly utility-driven such as the LM programs. DLC type is the most commonly addressed in LM programs [19–21]. In DLC programs, utility operators have the ability to remotely shut down customers' appliances on short notice in exchange for an incentive payment. Privacy and comfort of customers are behind the inefficiency and failure of such programs. An alternative for the DLC program is the TBP that is investigated extensively in the literature. TBPs use smart pricing to enable customers to rationally decide their electricity consumption aiming at reducing their electricity bills [22–27]. It has been argued that TBP is the most direct and efficient DSM technique and thus it should be investigated and used by policymakers [27]. Other studies have been conducted on DSM and its techniques in [8, 9, 13, 14, 28, 29]. Moreover, several DSM projects and pilots have been developed in countries such as Canada, Germany, Australia, Japan, China, and Vietnam [30–36].

In order to overcome the challenges of implementing DSM such as large control overhead on utilities, difficultly of manually responding to hourly changing prices by customers, and load synchronization, ADSM has been recently proposed.

An extensive literature has been performed on ADSM based smart pricing in SSMC and MSMC systems. One thread of research, namely individual ADSM, aims at managing every customer's load in order to minimize the consumption expenditures or the load profile PAR, and\or increase the penetration of RESs [37–46]. In this configu-

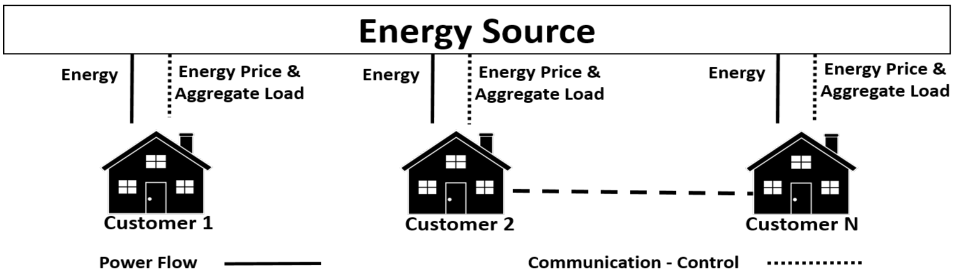


Figure 2: An individual ADSM System.

ration, utilities encourage customers to voluntarily and individually follow certain rules based on a smart pricing strategy, e.g., reducing the consumption at high price hours. Each customer's smart meter receives the electricity prices and shares the load with the grid through a two-way communication infrastructure, as shown in Fig. 2. Several optimization approaches are used to achieve the objectives of this configuration such as integer programming, dynamic programming, sequential quadratic programming, particle swarm optimization, etc [47–52]. The major downside of this mechanism is that it requires high computational capabilities at grid side, which is neither efficient nor scalable. In addition, the impact of each customer's consumption behavior on the system overall performance and on other customers' bill payments is not taken into consideration.

Another thread of research has been investigated recently, namely group ADSM, focuses on managing the aggregate energy consumption of a group of customers connected to a shared energy source and/or to DESs/DSEs through the utilization of advanced communication networks as shown in Fig. 3. The main objectives of implementing group ADSM programs are minimizing the total system cost or minimizing the PAR of the system load profile and/or increasing the penetration of RESs [53–62]. In contrast to individual ADSM, the impact of a customer's consumption behavior on all other customers' energy expenditures and the system, in general, is considered. A common and effective analytical tool used in this method is game theory [63]. Both cooperative and non-cooperative game-theoretic techniques are utilized to achieve the system-wide objectives. For example, the authors in [53] devised a congestion energy scheduling game to minimize the total system cost. In [64], a Stackelberg consumption game is used to model the complicated interactions between the utility and its customers

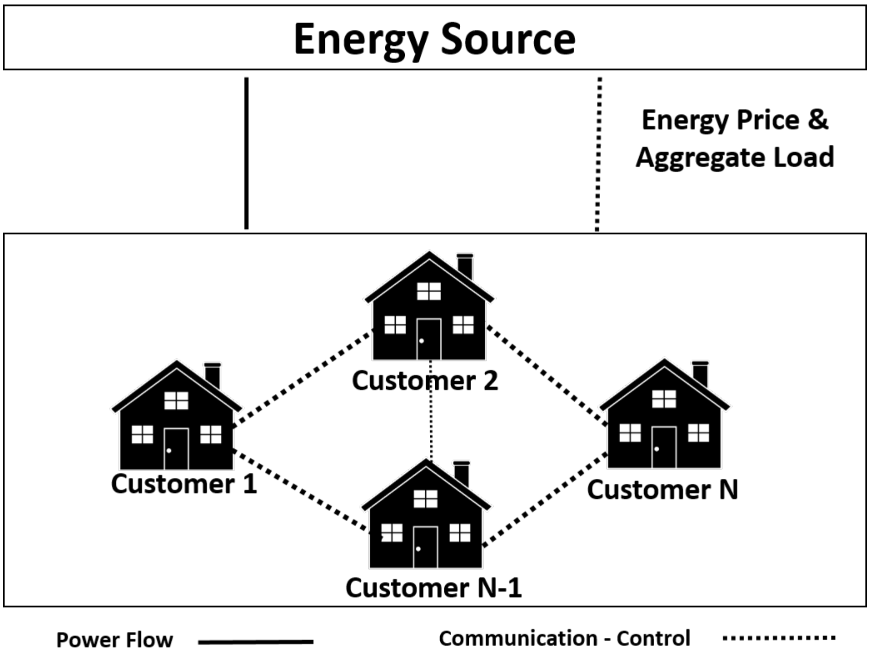


Figure 3: A group ADSM System.

to maximize the utility profit and customers' payoffs. The work in [65] addresses a group ADSM system in competitive and oligopolistic markets. In both markets, the proposed game achieves the optimal equilibrium gradually.

A few works have been performed using the group ADSM mechanism in MSMC systems in microgrids. In [59], a group ADSM program is investigated using dynamic potential game in order to minimize the total system cost and increase the penetration of wind energy. An isolated microgrid with a centralized wind farm is considered and conventional resources are used only if the predicted wind power does not meet the load. It is worth to mention that the use of DSEs are not considered. In [66], customers' interactions are modeled as a repeated energy consumption game where customer's behavior is characterized by Bayesian NE. The authors in [67] apply an auction game to find the optimal operating strategy of different types of generators to minimize the total operating cost and greenhouse emissions in a microgrid. A dynamic game is proposed in [68] to determine the optimal energy trading amounts among the different parties of the system including RESs. In [69], a Stackelberg game is formulated to minimize the system cost and secure the power supply of the microgrid. By this game, the percentages of available power and storage are decided such that the stresses on the loads are reduced. Both non-cooperative and cooperative game-theoretic models are built for the planning of a hybrid power system in a microgrid in [70]. Some other works under the umbrella of group ADSM are addressed in [2, 3, 71–83].

In most of the prior works in the literature, the group ADSM programs are successful in achieving the grid objectives. However, most of these works ignore that in reality the success of group ADSM programs relies on the active participation and satisfaction of customers. These works fall-short addressing fairness as a powerful tool to increase the level of customers' participation and achieve system objectives. Up to our knowledge, only the works in [2, 3, 72–76, 82, 83] have addressed fairness in designing their group ADSM programs but with different perspectives. In [72], fairness is defined as assigning the same long-term average delay to every customer, which may not be practical in many cases. The authors in [73] present a group ADSM model that charges customers based on their income level and types of appliances. Generally, this criterion is not appealing to customers as it raises privacy concerns. In [2], a billing model that charges customers in proportion to their total daily electricity consumption in a group ADSM system, is proposed. A major drawback of the proposed model is not considering the customers' exact load profiles, i.e., if two customers have equal total daily load, they will pay equally regardless of their load profiles. To address this problem, [3, 74–76, 82, 83] suggested a billing mechanism, where each customer is charged based on flexibility share in achieving the system optimality, which can effectively improve the fairness level of the system. One of the main drawbacks of the models in [2, 3, 72, 74–76, 82, 83] lies in not considering the impact of customers' violations after assigning the consumption schedules on the system fairness level. This drawback is mainly due to the type of billing model adopted which penalizes all customers in the system if a customer does not abide by the assigned system schedules. This makes the system unfair in the sense that the contribution to the system optimality is not considered in the case of violations.

In addition, the existing body of work on group ADSM in SSMC and MSMC systems tends to make restrictive assumptions and employ simplified mathematical system models which do not reflect real life consumption scenarios. Moreover, most of literature works assume that smart meters can handle a huge number of complex operations to compute the optimal consumption schedules, which is not a practical assumption as the computational capability of smart meters is limited. Mainly, such issues are tackled in individual ADSM systems using several heuristic and evolutionary techniques [84–86]. Up to our knowledge, none of the works in the literature has considered the computational limitations of group ADSM in MSMC systems in microgrids. As for SSMC systems, only the work [87] has investigated this issue by using P-MCTS method in order to solve the energy consumption game. However, the system model and appliances descriptions are very simplified and there is no indication of system complexity and computational time. In this work, the TS method is utilized, which is a meta-heuristic method proposed by Glover in 1989 [17]. The TS method has superior performance in terms of computational complexity and time and accuracy of results in the field of resources scheduling compared to other heuristic techniques as shown in [88–91]. So TS is proposed to be applied on the energy consumption scheduling game problem with the hope of obtaining optimal results and less computationally demanding operations. Furthermore, one of the major advantages of TS is the ability to escape the trap of local optimality by the utilization of variable memory structures [18]. In addition, it has remarkable achievements for various combinatorial problems in the fields of computer games, artificial intelligence, optimization problems, planning and learning [92–97].

In this work, an energy consumption scheduling algorithm based on TS is proposed to efficiently compute the energy consumption schedules of all customers in the SSMC and MSMC systems such that the total systems cost is reduced. In addition, as an alternative to the billing mechanisms in [2, 3, 72–76, 82, 83], an energy consumption billing mechanism that takes into account the impact of violations on the SSMC and MSMC systems performance and how to deal with them to ensure a higher level of fairness, is proposed. Furthermore, a novel energy consumption scheduling strategy is proposed to tackle the intermittent nature of solar energy generation through the implementation of a DEM mechanism combined with an aggregative game in an isolated microgrid. According to [98], distributed rooftop PVs and DSEs owned by households make the penetration of energy 30% more efficient than by using centralized units. Thus, in this study, each household is equipped with a rooftop PV panel and a storage device unlike other works where centralized RESs and DSEs are utilized. Practically speaking, the amount of harvested solar energy during a time interval mostly does not exceed the total consumption required by a customer and hence using DEM is more computationally efficient than considering the aggregative game alone as always considered in the literature.

Chapter 3: Energy Consumption Scheduling for a Single-Source Multiple-Customers (SSMC) System

3.1. Introduction

In this chapter, an efficient and fair group ADSM program in the SSMC system, is proposed. The program aims at reducing the total system generation cost. First, the SSMC system model and residential load control, are illustrated. Then, a fair energy consumption billing mechanism, is proposed. Each customer is charged based on the contribution to the program success and the total energy consumption. An energy consumption scheduling algorithm based on TS, is developed. Finally, numerical and simulation results for case studies are provided to demonstrate the effectiveness of the proposed program.

3.2. The SSMC System Model

In this section, the analytical description of the SSMC system model is presented. Fig. 4 depicts the system which consists of an energy source (e.g., a generator or a step-down substation transformer) shared by multiple customers. It is assumed that each customer's household is equipped with a smart meter, which is considered as the external interface with the utility, and all other customers. The meter is capable of collecting a customer's power consumption requirements, communicating with system parties, and computing energy consumption schedules using the ECS capability. Furthermore, all smart meters are assumed to be connected to two-way flow of power and communication networks. Denote the set of customers by $\mathcal{N} = \{1,..,n,...,N\}, n \in \mathcal{N}$, where N is the total number of customers. The set of household appliances is defined as $\mathcal{A}_n = \{1,..,a_n,...,A_n\}$, $a_n \in \mathcal{A}_n$ and each time-slot during the period of analysis is denoted as $h \in \mathcal{H}$, $\mathcal{H} = \{1,..,h,...,H\}$ where H is the total number of time-slots. Without loss of generality, it is assumed that each smart meter schedules the energy consumption for a period of one day, $H = 24$, in advance, and time granularity of one hour.

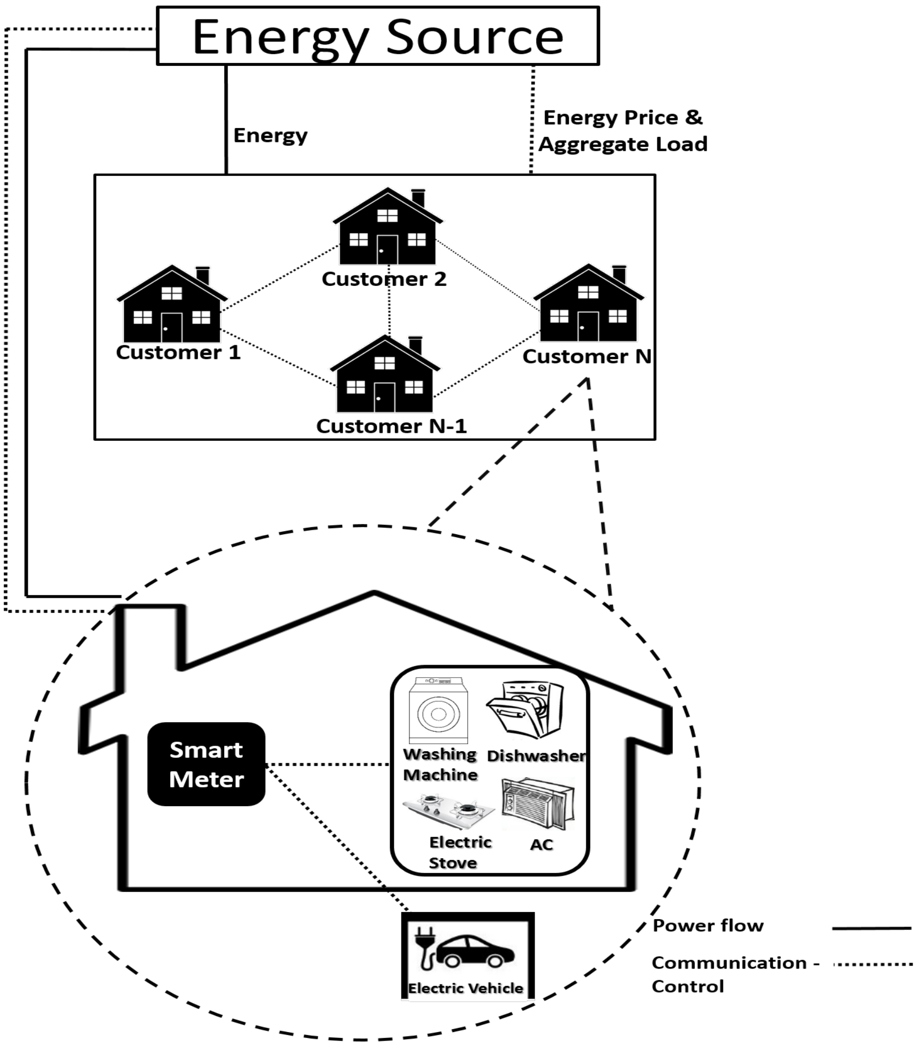


Figure 4: The SSMC system model.

For each customer n, the energy load profile matrix of all appliances a_n in H time-slots is denoted by

$$\mathfrak{X}_n = [\boldsymbol{x}_{n,1}, ..., \boldsymbol{x}_{n,A_n}] \in \mathbb{R}^{(H \times A_n)} \tag{1}$$

where the energy load profile for each appliance a_n is

$$\boldsymbol{x}_{n,a_n} = [x^1_{n,a_n}, .., x^h_{n,a_n}, .., x^H_{n,a_n}]^T. \tag{2}$$

It should be noted that the unit of x^h_{n,a_n} is kWh.

In this work, two types of appliances are considered: shiftable and non-shiftable appliances. The non-shiftable appliances, such as lighting and refrigerators, have fixed routine of operations that cannot be controlled by the smart meter and its ECS functionality. The meter will ensure continuous supply of power under all circumstances [99]. In contrast, the shiftable appliances can be controlled by the smart meter and are divided into time-shiftable and adjustable appliances. For time-shiftable appliances, such as washing machines and dryers, the operational time-slot can be shifted but without varying the amount of power consumption during the slot. As for adjustable appliances, such as electric vehicles, both the operational time-slot and the power can be varied.

For each customer $n \in \mathcal{N}$, the set of non-shiftable appliances is denoted as

$$\mathcal{A}_{n_s} = \{1, ..., a_{n_s}, ..., A_{n_s}\}, a_{n_s} \in \mathcal{A}_{n_s} \subset \mathcal{A}_{n_s}, \tag{3}$$

the set of time-shiftable appliances is denoted as

$$\mathcal{A}_{n_t} = \{1, ..., a_{n_t}, ..., A_{n_t}\}, a_{n_t} \in \mathcal{A}_{n_t} \subset \mathcal{A}_{n_t}, \tag{4}$$

and the set of adjustable appliances is denoted as

$$\mathcal{A}_{n_d} = \{1, ..., a_{n_d}, ..., A_{n_d}\}, a_{n_d} \in \mathcal{A}_{n_d} \subset \mathcal{A}_{n_d}. \tag{5}$$

It can be noted that $\mathcal{A}_n = \mathcal{A}_{n_s} \cup \mathcal{A}_{n_t} \cup \mathcal{A}_{n_d}$ and a_n is a generalized notation which represents any of the appliances types.

At each hour $h \in \mathcal{H}$, the electricity generation cost is determined by the following thermal generators cost function [100],

$$C(L^h) = \zeta^h L^{h^2} + \varepsilon^h L^h + \upsilon^h, \tag{6}$$

where $L^h \geq 0$ is the total system load, i.e, $L^h = \sum_{n=1}^{N} \sum_{a_n=1}^{A_n} x^h_{n,a_n}$. Also, ζ^h(cents/kW) > 0, ε^h(cents/kW), and υ^h(cents/kW) ≥ 0 are the fuel cost coefficients of the generator, at each hour $h \in \mathcal{H}$.

It should be noted that the cost function in (42) is an increasing and convex function which ensures that the cost can grow rapidly as the aggregated load increases. This can effectively convince customers to shift their load from peak hours to non-peak hours, thereby flattening the overall load curve and reducing the total generation cost.

3.3. Residential Load Control

The main task of each customer's smart meter is to determine the optimal energy consumption schedule $\mathfrak{X}_n$. In this section, the constraints and the feasible choices of the energy consumption schedules based on customers' preferences, are identified.

Each customer is required to specify the beginning $\boldsymbol{\alpha}_{a_n}$ and the end $\boldsymbol{\beta}_{a_n}$ of the set of preferred intervals over which an appliance can be scheduled, where

$$\boldsymbol{\alpha}_{a_n} = \{\alpha_{a_n,1}, \ldots.., \alpha_{a_n,W_{a_n}}\},\ w_{a_n} \in \mathcal{W}_{a_n} = [1, 2, \ldots., W_{a_n}], \tag{7}$$

and

$$\boldsymbol{\beta}_{a_n} = \{\beta_{a_n,1}, \ldots.., \beta_{a_n,W_{a_n}}\},\ w_{a_n} \in \mathcal{W}_{a_n} = [1, 2, \ldots., W_{a_n}], \tag{8}$$

where $\mathcal{W}_{a_n}$ is the set of preferred intervals for an appliance a_n. It should be noted that these intervals are chosen based on the customer's preferences. Clearly,

$$\boldsymbol{\beta}_{a_n,w_{a_n}} \geq \boldsymbol{\alpha}_{a_n,w_{a_n}},\ a_n \in \mathcal{A}_n,\ w_{a_n} \in \mathcal{W}_{a_n}. \tag{9}$$

For each customer n, the predetermined daily energy consumption for appliance a_n is denoted as E_{n,a_n}. The scheduled daily energy consumption for appliance a_n is equal to its predetermined daily consumption, that is

$$\sum_{w_{a_n}=1}^{W_{a_n}} \sum_{h=\alpha_{a_n,w_{a_n}}}^{\beta_{a_n,w_{a_n}}} x^h_{n,a_n} = E_{n,a_n},\ x^h_{n,a_n} = 0,\ \forall h \in \mathcal{H} \backslash \mathcal{H}_{a_n}, \forall a_n \in \mathcal{A}_n, \forall n \in \mathcal{N}, \tag{10}$$

where $\mathcal{H}_{a_n} \equiv [\boldsymbol{\alpha}_{a_n}, \boldsymbol{\beta}_{a_n}]$, i.e., all time-slots that are within the set of preferred intervals $k_{a_n} \in \mathcal{K}_{a_n}$. The mathematical operator "$\backslash$" means "except".

It should be noted that the total electricity consumption during a day does not change as the aim of the work is to shift the load not to reduce it.

For each appliance a_n, the preferred interval provided by each customer needs to be larger than or equal to the interval needed to finish the operation. Let $\boldsymbol{\Delta}_{a_n}$ be the time needed for an appliance a_n to finish its operation. Then,

$$\boldsymbol{\Delta}_{a_n} \leq \boldsymbol{\beta}_{a_n} - \boldsymbol{\alpha}_{a_n}, \forall a_n \in \mathcal{A}_n. \tag{11}$$

The minimum standby power level for each appliance a_n is denoted as $\lambda_{a_n}^{min}$, and its maximum power level as $\lambda_{a_n}^{max}$. Standby power refers to the power consumed by each appliance while it is switched off or it is in a standby mode. Then,

$$\lambda_{a_n}^{min} \leq x_{n,a_n}^{h} \leq \lambda_{a_n}^{max},\ \forall h \in \mathcal{H}_{a_n}, \forall a_n \in \mathcal{A}_n, , \forall n \in \mathcal{N}. \tag{12}$$

As previously mentioned, the operation of the non-shiftable appliances has strict energy consumption scheduling constraints. For example, a freezer may have to be on all the time. In that case, $\alpha_{a_{ns},w_{a_{ns}}} = 1$ and $\beta_{a_{ns},w_{a_{ns}}} = 24$. Furthermore, the hourly power requirement is fixed at $\delta_{a_{ns},w_{a_{ns}}}^{h}$ during its working period such that

$$x_{n,a_{ns}}^{h} = \delta_{a_{ns},w_{a_{ns}}}^{h}, \forall h \in \mathcal{H}_{a_{ns}}. \tag{13}$$

As for adjustable appliances, the power consumption may vary within the range in,

$$\lambda_{a_{n_d}}^{min} \leq x_{n,a_{n_d}}^{h} \leq \lambda_{a_{n_d}}^{max},\ \forall h \in \mathcal{H}_{a_{n_d}}, \tag{14}$$

depending on the type of the appliance and customers' preferences.

For any time-shiftable appliance a_{n_t} that consumes $E_{n,a_{n_t}}$, if only the constraints (9), (10), (11), and (12) are imposed, then the energy consumption schedule will ensure supply of $E_{n,a_{n_t}}$ over the preferred set of intervals $[\boldsymbol{\alpha}_{a_{n_t}}, \boldsymbol{\beta}_{a_{n_t}}]$. For example, if an appliance requires 2 kWh to finish its operation, the resultant schedule should ensure 2 kWh energy supply at the end of the interval, however, this power can be distributed in any possible way. For example, the consumption vector can have 0.5 kW for two hours, 0.25 kW for another 4 hours and zeros for the rest. Mostly, time-shiftable appliances cannot operate in such manner as they have fixed power consumption patterns. For example, it may require fixed 1.5 kW for the first hour and another 0.5 kW for the second hour of operation. Hence, the constraints in (9), (10), (11), and (12) alone are not sufficient to ensure feasible energy scheduling for time-shiftable appliances. The fixed power consumption pattern constraint of time-shiftable appliances can be modeled as follows. First, it is important to notice that all the previous constraints are formulated using linear programming, which cannot formulate the last discussed constraint. In order to deal with this constraint, a non-linear mixed-integer programming framework is applied. For each time-shiftable appliance a_{n_t}, define a fixed consumption pattern as $\boldsymbol{\pi}_{a_{n_t}} = [\pi^1_{a_{n_t}}, \pi^2_{a_{n_t}}, ..., \pi^H_{a_{n_t}}]^T$ and a binary integer vector as $\boldsymbol{y}_{a_{n_t}} = [y^1_{a_{n_t}}, y^2_{a_{n_t}}, ..., y^H_{a_{n_t}}]^T, y^h_{a_{n_t}} \in \{0,1\}$, where 0 and 1 indicate that the appliance is off and on, respectively. The vector $\boldsymbol{y}_{a_{n_t}}$ is used as the control switch for the time-shiftable appliance. Moreover, let

$$\boldsymbol{\Pi}_{a_{n_t}} = \begin{bmatrix} \pi^1_1 & \pi^2_1 & \pi^3_1 & \dots & \pi^H_1 \\ \pi^1_2 & \pi^2_2 & \pi^3_2 & \dots & \pi^H_2 \\ \dots & \dots & \dots & \dots & \dots \\ \pi^1_{A_{n_t}} & \pi^2_{A_{n_t}} & \pi^3_{A_{n_t}} & \dots & \pi^H_{A_{n_t}} \end{bmatrix}$$

be the cyclic shifts of the pattern $\boldsymbol{\pi}_{a_{n_t}}$. The schedule $\boldsymbol{x}_{n,a_n}$ has to be one of the cyclic shits in $\boldsymbol{\Pi}_{a_{n_t}}$. Therefore, the consumption schedule for a time-shiftable appliance can be written as

$$\boldsymbol{x}_{n,a_{n_t}} = \boldsymbol{\Pi}_{a_{n_t}} \boldsymbol{y}_{a_{n_t}}. \tag{15}$$

3.4. Energy Consumption Billing Mechanism

In this work, the billing mechanism proposed in [2] is utilized and improved. This billing mechanism satisfies the two assumptions below.

- Let b_n denote the daily energy bill for each customer $n \in \mathcal{N}$. b_n should represent the customers' total energy bill and relate it to the total system generation cost, that is.

$$\sum_{n=1}^{N} b_n \geq \sum_{h=1}^{H} C(L^h), \tag{16}$$

where the left-hand side is the total daily bill for all customers and the right-hand side is the total system daily generation cost. Without loss of generality, throughout the work, the billing mechanism is assumed to be budget balance, i.e., $\sum_{n=1}^{N} b_n = \sum_{h=1}^{H} C(L^h)$.

- It is further assumed that every customer's bill is affected by the total load of all other customers in the system. That is, a customer is charged in proportional to his daily load and all others' daily load. Mathematically speaking,

$$\sum_{m=1}^{N} b_m = b_n \frac{\sum\limits_{h=1}^{H} L^h}{\sum\limits_{a_n=1}^{A_n} E_{n,a_n}}, \forall n \in \mathcal{N}. \tag{17}$$

The energy billing mechanism that satisfies both assumptions in (16) and (17) is as follows,

$$b_n = \psi_n \sum_{h=1}^{H} C\left(L^h - \sum_{a_n=1}^{A_n} x_{n,a_n}^h\right), \forall n \in \mathcal{N}, \tag{18}$$

where $\psi_n = \frac{\sum\limits_{a_n=1}^{A_n} E_{n,a_n}}{\sum\limits_{h=1}^{H} L^h}$.

3.4.1. Fair billing mechanism. Each smart meter provides each customer with the near-optimal energy consumption schedules based on the minimization of the billing mechanism in (18). A common assumption in the literature is that all customers who decide to participate in ADSM programs would fully commit to the assigned schedules by the smart meters. The usual argument that supports this assumption is that since customers benefit financially from abiding by the assigned schedules, there would be no reason to violate them. However, this assumption is not always true, and violations could happen any time after announcing the assigned schedules. This requires the increase of energy generation that increases the cost of energy during the violation time. Up to our knowledge, all the works in the literature have considered that the extra cost caused by customers' violations is divided among all customers. This would have a negative impact on the fairness level of the ADSM program as customers who abide by their schedules and those who do not are both equally penalized. In this work, this violation penalty fairness aspect is considered. The violation cost is divided only among customers who do not abide by their schedules. In addition to achieving fairness between violators and non-violators, it is important to guarantee fairness among violators themselves.

3.4.2. Alternative billing mechanism. In this work, a fair billing mechanism to address how system violations should be dealt with is proposed and investigated. In order to distribute the increase in the cost of energy among the customers who violate the assigned schedules, the penalty factor for customer n at $h \in \mathcal{H}$ is calculated by,

$$P_v^h = \frac{l_n^h - l_n^{h*}}{\sum_{i=1}^{V} (l_i^h - l_i^{h*})}, \; v \in \mathcal{V}, \tag{19}$$

where l_n^h is the actual hourly load after assigning the schedules of customer n, l_n^{h*} is the near-optimal hourly scheduled load of customer n, and $\mathcal{V} = [1, ...v, ...V]$ is the set of violators at $h \in \mathcal{H}$. The penalty factor for non-violators at $h \in \mathcal{H}$,

$$P_v^h = 0. \tag{20}$$

The bill for any customer n at $h \in \mathcal{H}$,

$$b_n^h = b_n^{h*} + P_v^h(C(L^h) - C(L^{h*})), \tag{21}$$

where b_n^{h*} is the hourly bill if customer n abides by the assigned consumption schedule. $C(L^h)$ is the actual total system generation cost and $C(L^{h*})$ is the total near-optimal system generation cost at $h \in \mathcal{H}$.

The end of day bill for customer n is

$$b_n = \sum_{h=1}^{H} b_n^h. \tag{22}$$

In the aftermath, all customers who abide by their schedules do not get penalized or affected by violations of others. Furthermore, fairness among violators themselves is maintained as the penalty factor is proportional to the amount and time of the violation.

3.5. Energy Consumption Aggregative Game Formulation

In this section, an aggregative energy consumption game to model the strategic behavior of the customers in the SSMC, is investigated. All customers are assumed to be selfish as they need to minimize their individual energy bills through the scheduling of a day-ahead energy consumption. In particular, each customer n aims to minimize the total energy bill through the minimization of the total system cost in (18). As illustrated in (18), each customer's bill depends on how he and all other customers schedule their consumption which naturally leads to the formulation of the following aggregative energy consumption game.

- Players: customers in set $\mathcal{N}$.
- Strategies: each customer n selects the consumption profile $\mathfrak{X}_n$ that maximizes the payoffs and satisfies all the constraints.
- Payoffs: for each customer n, the payoff function is $-b_n^*$, where b_n^* is the total daily electricity bill.

where

$$b_n^* = \psi_n \min_{\mathfrak{X}_n} \sum_{h=1}^{H} C\left(L^h - \sum_{a_n=1}^{A_n} x_{n,a_n}^h\right), \tag{23}$$

subject to

$$\boldsymbol{\beta}_{a_n,w_{a_n}} \geq \boldsymbol{\alpha}_{a_n,w_{a_n}},\ a_n \in \mathcal{A}_n,\ w_{a_n} \in \mathcal{W}_{a_n},$$

$$\sum_{w_{a_n}=1}^{W_{a_n}} \sum_{h=\alpha_{a_n,w_{a_n}}}^{\beta_{a_n,w_{a_n}}} x_{n,a_n}^h = E_{n,a_n},\ x_{n,a_n}^h = 0,\ \forall h \in \mathcal{H} \backslash \mathcal{H}_{a_n}, w_{a_n} \in \mathcal{W}_{a_n},$$

$$\boldsymbol{\Delta}_{a_n} \leq \boldsymbol{\beta}_{a_n} - \boldsymbol{\alpha}_{a_n},$$

$$\lambda_{a_n}^{min} \leq x_{n,a_n}^h \leq \lambda_{a_n}^{max},\ \forall h \in \mathcal{H}_{a_n},$$

$$x_{n,a_{n_s}}^h = \delta_{a_{n_s},w_{a_n}}^h, \forall h \in \mathcal{H}_{a_{n_s}},$$

$$\lambda_{a_{n_d}}^{min} \leq x_{n,a_{n_d}}^h \leq \lambda_{a_{n_d}}^{max},\ \forall h \in \mathcal{H}_{a_{n_d}},$$

$$\boldsymbol{x}_{n,a_{n_t}} = \boldsymbol{\Pi}_{a_{n_t}} \boldsymbol{y}_{a_{n_t}}.$$

It is worth pointing out that the (23) function is a nonlinear mixed-integer optimization model, where the non-linearity in the model is attributed to the quadratic term in the function. As a result, the aggregative game should be treated as a non-continuous game. The existence and uniqueness of the Nash Equilibrium (NE) points cannot be guaranteed as in some of the continuous games. There may be one, none or multiple NE points in the game. However, in this work, the effectiveness of the aggregative game is demonstrated through numerical and simulation results.

3.6. Energy Consumption Scheduling Algorithm Based on Tabu Search (TS)

As a result of the different domains of the variables of each individual customer's schedule (i.e., integer and continuous variables), the energy consumption problem in (23) is a nonlinear mixed-integer optimization problem, which is known as NP-hard. A variety of exhaustive search techniques could be used to solve NP-hard problems such as the BB [101]. However, these exhaustive techniques are neither efficient nor practical as their computational time and complexity increase exponentially with the increase in the problem size. This section develops an efficient heuristic energy consumption scheduling algorithm based on TS. In addition to the ability of achieving the near-optimal energy schedules, the computational time is reduced by hundred multiples compared to the benchmark energy consumption scheduling algorithm based on BB. In this work, the term "near-optimal" is defined based on the result of the algorithm based on BB, as it is an exhaustive search technique that can reach the optimal point of the algorithm but on the expense of computational time. Also. the convergence of the proposed algorithm is decided upon the convergence of the algorithm based on BB.

At each TS iteration of the optimization of each customer's schedule, a variety of solutions that are neighbors' of the current solution are generated and evaluated in terms of the cost. By employing a variable memory structure of recent candidate solutions, TS is able to escape from a local optimum and explore other regions of the search space.

The energy consumption algorithm based on TS that is run in each customer's smart meter is shown in Algorithm 1. The Algorithm starts with a random initial energy schedule for all customers in the system except for customer n ($\forall m \in \mathcal{N} \backslash \{n\}$). Each customer's smart meter solves the optimization problem in (23) using the TS method in Algorithm 2. The resultant total load at each hour is broadcasted to all other customers and the loop is executed until no updated schedules are announced. At the end of H time-slots, customers are charged based on the billing mechanism in (22) to assure that system violations are treated in a fair manner.

For each customer n, the output of the heuristic method in Algorithm 2 is an energy consumption schedule described by the two lists denoted as $\mathfrak{T}$ and $\mathfrak{Q}$. The list $\mathfrak{T}$ contains the operational time-slots for the set of appliances $\mathcal{A}_n$ and the list $\mathfrak{Q}$ contains the power consumption for the set of appliances $\mathcal{A}_n$ for all operational times.

The first step of the heuristic method is to generate an initial schedule (initial guess) by relaxing the integer constraints and variables of the nonlinear mixed-integer problem in (23) to continuous variables, which converts the problem to a convex problem that can be solved using Interior Point Method (IPM) technique [102]. The relaxed problem formulation contains only continuous variables and applies the constraints of the original problem in (23) except (15). Clearly, the output consumption schedule guarantees feasible energy consumption for the non-shiftable and adjustable appliances. However, the time-shiftable appliances consumption is not guaranteed to be feasible as (15) is not always satisfied. Now, the output schedule of the time-shiftable appliances $(\mathfrak{T}, \mathfrak{Q})_{a_{n_t}}$ of the resultant relaxed problem is tested to check whether the constraints in (9), (10), (11), (12), (13), (14) are satisfied or not, using Algorithm 3. If the output $(\mathfrak{T}, \mathfrak{Q})_{a_{n_t}}$ is feasible, then $(\mathfrak{T}, \mathfrak{Q})$, i.e., the output schedule of all appliances, is considered as the global optimal schedule of the system and the process is terminated. If not, which is usually the case, the scheduled consumption of non-shiftable and adjustable appliances are considered as fixed quantities. The schedules of time-shiftable appliances are randomly generated as such all constraints are satisfied. Once a feasible schedule $(\mathfrak{T}, \mathfrak{Q})$ is generated, the process of the TS begins. This initialization method is used to unify the initial guesses of the TS, BB and P-MCTS methods for fair comparison. It should be highlighted that this method of initialization is shown to result in nearer to optimal solutions than the fully randomized method, as per our numerical simulations.

Now, $\mathfrak{T}$ and $\mathfrak{Q}$ are added to the Tabu lists $\boldsymbol{TL}_{\mathfrak{T}}$ and $\boldsymbol{TL}_{\mathfrak{Q}}$, respectively, that are named as such as the schedules they contain are not used as performance benchmarks. Now, the generation of the neighboring solutions of the current solution $(\mathfrak{T}, \mathfrak{Q})$ starts as follows. A total of G neighbors, not all of which are necessarily feasible, are generated. Depending on the type of the appliance, each of these neighbors is formed through one of the following possible operations:

- For time-shiftable appliances

1. Randomly swap two rows in $\mathfrak{T}_{a_{n_t}}$.
2. Randomly swap two elements in a column in $\mathfrak{Q}_{a_{n_t}}$.

- For adjustable appliances

1. Randomly swap two rows in $\mathfrak{T}_{a_{n_d}}$.
2. Randomly swap two elements in a column in $\mathfrak{Q}_{a_{n_d}}$.
3. Randomly shift an element in a column in $\mathfrak{Q}_{a_{n_d}}$.
4. Randomly shift an element in two columns in $\mathfrak{Q}_{a_{n_t}}$.
5. Randomly vary the amount of consumption of elements in a column in $\mathfrak{Q}_{a_{n_t}}$.

As previously mentioned, the smart meter does not have any control over the operation of non-shiftable appliances so their energy consumption are considered as fixed quantities during the formulation of the schedules, i.e., no need to schedule them. A summary of the neighbors generation operations is shown in Algorithm 4.

After generating the neighboring schedules, they are checked if they satisfy the constraints in (9-15); infeasible solutions are simply discarded. Then, the feasible solutions are tested according to the objective function in (23) that measures the total bill of a customer. The best neighbor schedule is selected as the one which yields the system minimum total cost. This schedule is added to the Tabu lists and set as the current solution and the above sequence of operations are repeated until there is no decrease in the total cost or the number of iterations exceeds Z. Once the energy schedule with the minimum cost is chosen, it is broadcasted to all other customers and Algorithm 1 continues until the system near-optimal cost objective is satisfied.

It is worth mentioning that as all other heuristic optimization techniques, the optimality of the TS method cannot be proven nor guaranteed [18]. Thus the convergence

Algorithm 1 Energy Consumption Game: Executed by each customer $n \in \mathcal{N}$.

Randomly initialize $l_m^h, \forall m \in \mathcal{N} \backslash \{n\}, \forall h \in \mathcal{H}$
repeat
  At random time instances $\boldsymbol{D_o}$
    Run Algorithm 2 to solve (23)
      if $\mathfrak{X}_n$ changes compared to current schedule
        Update $\mathfrak{X}_n$ according to the new solution
        Broadcast a control message to announce $\mathfrak{X}_n$ to the other smart meters across the system
      end
  end
  if a control message is received **then**
    Update $L^h, \forall m \in \mathcal{N} \backslash \{n\}, \forall h \in \mathcal{H}$ accordingly
  end if
until No smart meter announces any new schedule
At $h = H$
for $h = 1 : 1 : H$ **do**
  if $l_n^h - l_n^{h*} = 0$ **then**
    $b_n^h = b_n^{h*} + P_v^h(C(L^h) - C(L^{h*}))$, $P_v^h = 0$
  else
    $b_n^h = b_n^{h*} + P_v^h(C(L^h) - C(L^{h*}))$, $P_v^h \neq 0$
  end if
end for

of the proposed algorithm cannot be proven. However, in this work, the effectiveness of the algorithm based on TS is demonstrated through numerical and simulation results. In addition, the accuracy of the algorithm results is shown to be very close to the benchmark algorithm based on BB as will be illustrated later on.

Table 1 presents the definition of the parameters introduced in Algorithms 1, 2, 3, and 4 which are not included in the text.

3.7. Simulation Results

3.7.1. Scenario setup. In this section, simulation results are presented in order to assess the performance of the proposed group ADSM program in the SSMC system. The simulations are performed on PCs with the configurations shown in Table 2. In the considered system, we have 30 customers ($N = 30$) scheduling their energy consumption for the next 24 hours. All customers have the same set of shiftable and non-

Algorithm 2 Heuristic Scheduling Overview.

Set $z = 0$, $M_{OLD} = 0$, $M_{NEW} = 1$, Feasibility_Flag $= 0$,$\mathfrak{T} \in \mathbb{R}^{H \times A_n}$, and $\mathfrak{Q} \in \mathbb{R}^{H \times A_n}$
Relax integer constraints and variables in (23)
$(\mathfrak{T}, \mathfrak{Q}) \Leftarrow$ apply IPM to solve the relaxed problem
Feasibility_Flag = CHECK_FEASIBILITY $(\mathfrak{T}, \mathfrak{Q})_{a_{n_t}}$
if Feasibility_Flag $= 0$ **then**
  while Feasibility_Flag $= 0$ **do**
    $\mathfrak{T}_{a_t} \Leftarrow \kappa_{a_{n_t}}$ Randomly generated list of time-slots from $[1, ..., H_{a_{n_t}}]$
    Sort the elements of $\mathfrak{T}_{a_{n_t}}$ in increasing order
    Feasibility_Flag = CHECK_FEASIBILITY$(\mathfrak{T}, \mathfrak{Q})_{a_{n_t}}$
  end while
else
  $\mathfrak{T}_{opt} \Leftarrow \mathfrak{T}$
  $\mathfrak{Q}_{opt} \Leftarrow \mathfrak{Q}$
end if
$\boldsymbol{TL}_{\mathfrak{T}} \Leftarrow \mathfrak{T}$
$\boldsymbol{TL}_{\mathfrak{Q}} \Leftarrow \mathfrak{Q}$
while $z \leq Z$ and $|M_{NEW} - M_{OLD}| \leq \eta$ **do**
  $\{\mathfrak{T}_1, \mathfrak{T}_2, ..., \mathfrak{T}_G, \mathfrak{Q}_1, \mathfrak{Q}_2, ...\mathfrak{Q}_G\} =$
GENERATE_NEIGHBORS $(\mathfrak{T}, \mathfrak{Q})$
  $g_{opt} \Leftarrow \min_g \sum_{h=1}^{H} C^h \Big(\mathfrak{T}_g, \mathfrak{Q}_g\Big)^h$
  $M_{NEW} \Leftarrow \sum_{h=1}^{H} C^h \Big(\mathfrak{T}_{g_{opt}}, \mathfrak{Q}_{g_{opt}}\Big)^h$
  if $M_{NEW} < M_{OLD}$ **then**
    $z \Leftarrow 0$
  else
    $z = z + 1$
  end if
  $M_{OLD} \Leftarrow M_{NEW}$
  $\boldsymbol{TL}_{\mathfrak{T}} \Leftarrow \{\boldsymbol{TL}_{\mathfrak{T}}, \mathfrak{T}_{opt}\}$
  $\boldsymbol{TL}_{\boldsymbol{C}} \Leftarrow \{\boldsymbol{TL}_{\mathfrak{Q}}, \mathfrak{Q}_{opt}\}$
  $\mathfrak{T} \Leftarrow \mathfrak{T}_{opt}$
  $\mathfrak{Q} \Leftarrow \mathfrak{Q}_{opt}$
end while

shiftable appliances. The set of appliances and their consumption specifications are listed in Table 3 [103]. As previously mentioned, the smart meters have only control over the time-shiftable and adjustable appliances. As for the non-shiftable appliances, they have strict consumption requirements that must be fulfilled all the time. The individual consumption patterns are formulated according to the constraints in (23). For example, for the fridge and freezer, a fixed amount of consumption has to be allocated

Algorithm 3 Function for Candidate Solution Feasibility Check.

Feasibility_Flag = CHECK_FEASIBILITY($\mathfrak{T},\mathfrak{Q}$)
Set Feasibility_Flag = 0
while $y \neq 0$ **do**
  for $a_n = 1:1:A_n \backslash \{\boldsymbol{\mathcal{A}}_{n_s}\}$ **do**
    for $w_{a_n} = 1:1:W_{a_n}$ **do**
      if $\sum_{h=\alpha_{a_n,w_{a_n}}}^{\beta_{a_n,w_{a_n}}} \mathfrak{Q}(h,a_n) = E_{a_n,w_{a_n}}$
&& $\beta_{a_n,w_{a_n}} \geq \alpha_{a_n,w_{a_n}}$ **then**
        $y = 1$
      else
        $y = 0$
      end if
      for $h = \alpha_{a_n,w_{a_n}} : 1 : \beta_{a_n,w_{a_n}}$ **do**
        if $\lambda_{a_n}^{min} \leq \mathfrak{Q}(h,a_n) \leq \lambda_{a_n}^{max}$ **then**
          $y = 1$
        else
          $y = 0$
        end if
        if $a_n \backslash \{\boldsymbol{\mathcal{A}}_{\boldsymbol{n}a_n}\}$ **then**
          if $\lambda_{a_n}^{min} \leq \mathfrak{Q}(h,a_n) \leq \lambda_{a_n}^{max}$ **then**
            $y = 1$
          else
            $y = 0$
          end if
        end if
      end for
      if $a_n \in \mathcal{A}_{n_t}$ **then**
        if $\mathfrak{Q}(:,a_{n_s}) = \boldsymbol{y}_{a_{n_t}} \odot \boldsymbol{\pi}_{a_{n_t}}$ **then**
          $y = 1$
        else
          $y = 0$
        end if
      end if
    end for
  end for
end while

all the time, i.e., $x_{n,a_n}^h = 0.2$ kW, $\forall h \in \mathcal{H}_{a_n}$. As for the electric vehicle (adjustable appliance), the allowed battery charger power consumption range is formulated as 0.2 kW $\leq x_{n,i_n}^h \leq$ 1kW$\forall h \in \mathcal{H}_{a_a}$. For the time-shiftable appliance, washing machine, the fixed power pattern is defined as $\boldsymbol{\pi}_{a_t} = [1, 0.5, 0, ...0]^T$, $\forall h \in \mathcal{H}_{a_t}$. The energy cost func-

Algorithm 4 Function for Generation of Neighboring Solutions.

FUNCTION $\{\mathfrak{T}_1, \mathfrak{T}_2, ..., \mathfrak{T}_G, \mathfrak{Q}_1, \mathfrak{Q}_2, ...\mathfrak{Q}_G\}$ = GENERATE_NEIGHBORS
for $g = 0 : 1 : G$ **do**
  $\mathfrak{T}_0 = \mathfrak{T}$
  $\mathfrak{Q}_0 = \mathfrak{Q}$
  $\boldsymbol{I} \Leftarrow$sample ($\mathcal{H}$, 2)*
  $\boldsymbol{I}_1 \Leftarrow$ sample ($\mathcal{A}_{n_s}$, 2)
  $\mathfrak{T}(\boldsymbol{I}(1), \boldsymbol{I}_1(1))_{g+1} \Leftarrow \mathfrak{T}(\boldsymbol{I}(2), \boldsymbol{I}_1(2))$
  $\mathfrak{T}(\boldsymbol{I}(2), \boldsymbol{I}_1(2))_{g+1} \Leftarrow \mathfrak{T}(\boldsymbol{I}(1), \boldsymbol{I}_1(1))$
  $\boldsymbol{I}_3 \Leftarrow$ sample ($\mathcal{H}$, 2)
  $\boldsymbol{I}_4 \Leftarrow$ sample ($\mathcal{A}_n$, 1)
  $\mathfrak{Q}_{a_{n_t}, a_{n_d}}(\boldsymbol{I}_3(1), \boldsymbol{I}_4(1))_{g+2} \Leftarrow \mathfrak{Q}_{a_{n_t}, a_{n_d}}(\boldsymbol{I}_3(2), \boldsymbol{I}_4(1))$
  $\mathfrak{Q}_{a_{n_t}, a_{n_d}}(\boldsymbol{I}_3(2), \boldsymbol{I}_4(1))_{g+2} \Leftarrow \mathfrak{Q}_{a_{n_t}, a_{n_d}}(\boldsymbol{I}_3(1), \boldsymbol{I}_4(1))$
  $\boldsymbol{I}_5 \Leftarrow$ sample ($\mathcal{H}$, 2)
  $\boldsymbol{I}_6 \Leftarrow$ sample ($\mathcal{A}_{n_s}$, 1)
  $\mathfrak{Q}_{a_{n_d}}(\boldsymbol{I}_5(1), \boldsymbol{I}_6(1))_{g+3} \Leftarrow \mathfrak{Q}_{a_{n_d}}(\boldsymbol{I}_5(2), \boldsymbol{I}_6(1)) + \mathfrak{Q}_{a_a}(\boldsymbol{I}_5(1), \boldsymbol{I}_6(1))$
  $\boldsymbol{I}_7 \Leftarrow$ sample ($\mathcal{H}$, 2)
  $\boldsymbol{I}_8 \Leftarrow$ sample ($\mathcal{A}_n$,2)
  $\mathfrak{Q}_{a_{n_d}}(\boldsymbol{I}_7(1), \boldsymbol{I}_8(1))_{g+4} \Leftarrow \mathfrak{Q}_{a_{n_d}}(\boldsymbol{I}_7(1), \boldsymbol{I}_8(1)) + \mathfrak{Q}_{a_{n_d}}(\boldsymbol{I}_7(2), \boldsymbol{I}_8(2))$
  $\boldsymbol{I}_9 \Leftarrow$ sample ($\mathcal{H}$, 2)
  $\boldsymbol{I}_{10} \Leftarrow$ sample ($\mathcal{A}_n$,1)
  $\boldsymbol{PE} \Leftarrow$ sample ($\{1/100, .., 100/100\}$,1)
  $\mathfrak{Q}_{a_{n_d}}(\boldsymbol{I}_9(1), \boldsymbol{I}_{10}(1))_{g+5} \Leftarrow (\boldsymbol{PE}) \times \mathfrak{Q}_{a_{n_d}}(\boldsymbol{I}_9(1), \boldsymbol{I}_{10}(1))$
  $\mathfrak{Q}_{a_{n_d}}(\boldsymbol{I}_9(2), \boldsymbol{I}_{10}(1))_{g+5} \Leftarrow (1 - \boldsymbol{PE}) \times \mathfrak{Q}_{a_{n_d}}(\boldsymbol{I}_9(1), \boldsymbol{I}_{10}(1)) + \mathfrak{Q}_{a_{n_d}}(\boldsymbol{I}_9(2), \boldsymbol{I}_{10}(1))$
end for
for $g = 1 : 1 : G$ **do**
  Feasibility_Flag = CHECK_FEASIBILITY ($\mathfrak{T}_g, \mathfrak{Q}_g$)
  if Feasibility_Flag = 0 **then**
    $\mathfrak{T}_g \Leftarrow \phi$
    $\mathfrak{Q}_g \Leftarrow \phi$
  end if
end for

* The function $\boldsymbol{I} = \{\text{sample}(Y, X)\}$ implies that the subset $\boldsymbol{I}$ contains X elements from the set Y , drawn randomly without replacement.

tion is assumed to be as in (42). The parameters values are $\zeta^h = 0.3, \varepsilon^h = 0.2$ and $\upsilon^h = 0.08$ cents during daytime hours (8:00 am to midnight) and $\zeta^h = 0.2$, $\varepsilon^h = 0.1$ and $\upsilon^h = 0.05$ cents during night hours (midnight to 8:00 am). Moreover, the billing system is assumed to be budget balanced, i.e, the total system cost is equal to the total bills of all customers.

Table 1: Algorithm 1, 2 ,3, and 4 parameters definition

Parameter	Definition
$\boldsymbol{D}_o$	Random time instance
z	Iteration number
Z	Total number of iterations
M_{OLD}	Total system cost at $(z-1)^{th}$ iteration
M_{NEW}	Total system cost at $(z)^{th}$ iteration
$\kappa_{a_{n_t}}$	Generated list of time-slots
η	Very small constant ≤ 0.0001
$\mathfrak{T}_{opt}$	Optimal operational time-slots list
$\mathfrak{Q}_{opt}$	Optimal power consumption list
y	Logic parameter, $y \in \{0,1\}$
$\mathfrak{Q}(h, a_n)$	An element in $\mathfrak{Q}$
$\mathfrak{Q}(:, a_n)$	A column in $\mathfrak{Q}$
$\mathfrak{T}_g$	g^{th} generated time-slots list
$\mathfrak{Q}_g$	g^{th} generated power consumption list
$\boldsymbol{I}_1$ - $\boldsymbol{I}_{10}$	Randomly generated lists/elements from $(\mathfrak{T}, \mathfrak{Q})$
$\boldsymbol{PE}$	Constant $\in [0.01, 1]$

In order to make the customers' load profiles as close as possible to practical profiles, the following procedure is followed. Fig. 5 provides a typical load profile for a residential customer [104]. First, for each customer $n \in \mathcal{N}$, the "Low limit" and "Upper limit" at each hour $h \in \mathcal{H}$ are formed by, respectively, adding a random real number to the corresponding value in Fig. 5. After that, the load profile of the customer at each hour h, is randomly chosen between the corresponding "Low limit" and "Upper limit". Our numerical results show that the total energy load of a customer ranges between 20 kWh to 45 kWh, which represents a typical residential customer load [104].

The timing in Algorithm 1 is based on a round-robin scenario. In this scenario, at each customer's turn, the local scheduling computation is performed and then the energy consumption schedule is updated. After that, the energy source gets informed about the customer's updated schedule, then randomly another customer is allocated for the next turn. This procedure continues until the convergence of Algorithm 1. By this mechanism, the energy source ensures that every customer takes a turn once in a while.

After incorporating all the constraints together, the energy consumption scheduling in Algorithm 1 is run based on the TS, BB, and P-MCTS methods. As for the

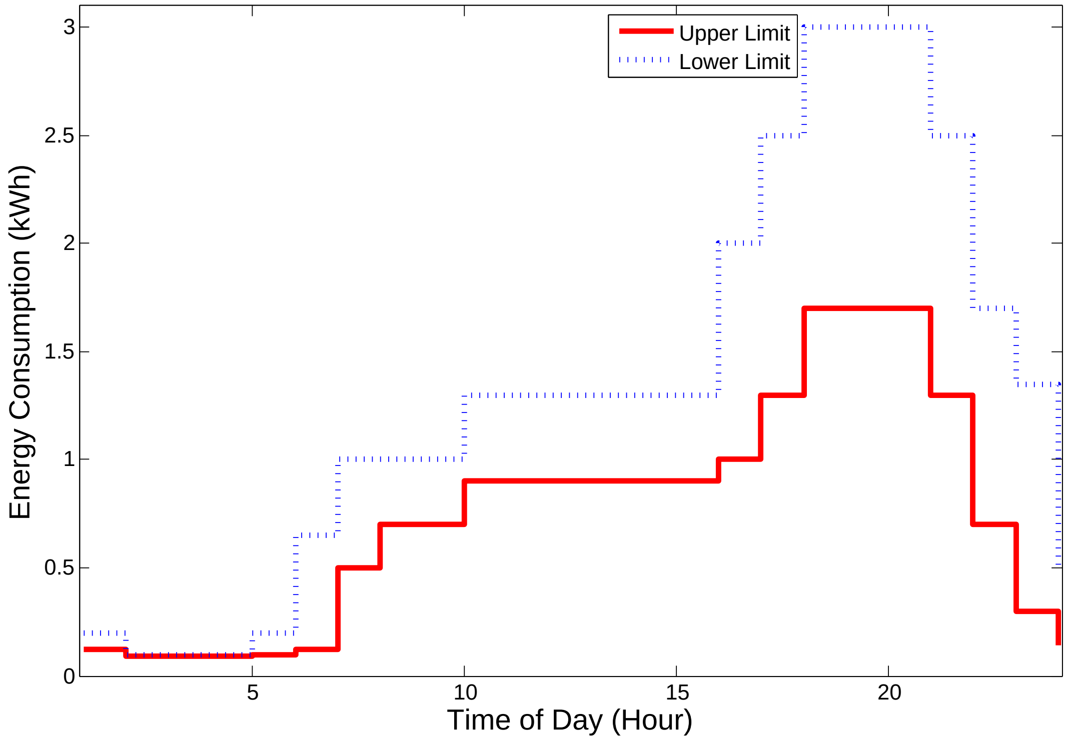


Figure 5: Typical energy consumption for customer n

Table 2: PC configurations

Processor	Intel (R) Core (TM) i7-3770S CPU@ 3.10 GHz 3.1 GHz
Installed Memory (RAM)	8.00 GB (7.89 GB usable)
System Type	64-bit operating system

P-MCTS method, the algorithm in [87] is run as proposed. In order to make a fair comparison between the three methods, the initial guess is unified. As previously mentioned, the initial guess is formalized through the relaxation of the integer constraints and variables in (23) such that the problem can be solved using IPM. The three methods are compared in terms of their computational time and results quality.

3.7.2. Results and discussion. Figures 6 and 7 show the total system energy consumption and the associated costs, respectively, for the cases when customer's n smart meter does not deploy an energy consumption scheduling algorithm, runs the algorithm based on TS, runs the algorithm based on BB, and runs the algorithm based on P-MCTS. All system constraints are fulfilled for the cases when the three algorithms are run in the smart meters. Clearly, both algorithms based BB and TS have almost

Table 3: The set of appliances and their power requirements.

Name	Type	Power Requirement
Microwave oven	Non-shiftable	1.5 kW
Refrigerator-freezer	Non-Shiftable	1.32 kW
LCD Television	Non-shiftable	0.23 kW
Energy kettle	Non-shiftable	2 kW
Lighting (10 standard bulbs)	Time-shiftable	1 kW
Clothes dryer	Time-shiftable	3.4 kW
Clothes iron	Time-shiftable	2.4 kW
Dishwasher	Time-shiftable	1.5 kW
Vacuum cleaner	Time-shiftable	1.6 kW
Washing machine	Time-shiftable	1.5 kW
Electric vehicle	Adjustable	0.34 kW per mile ($\lambda_1^{min} = 0.2$ kW,$\lambda_1^{max} = 3$ kW)
Water boiler	Adjustable	1.5 kW ($\lambda_2^{min} = 0.1$ kW, $\lambda_2^{max}1.5$ kW)

have converged to the same results, hence the convergence of the algorithm based on TS is achieved. As for the algorithm based on P-MCTS, the result is not as accurate as the algorithm based on TS, hence its convergence is not achieved.

As shown in Fig. 7 when the smart meter does not deploy an energy consumption scheduling algorithm, the PAR is 1.6303 and the total electricity consumption cost is \$227.9914. Moreover, when the algorithm based on TS is deployed in the smart meter, the total electricity consumption cost is \$194.9635 and the PAR is 1.2578. For the case when the smart meter deploys the algorithm based on BB, the total electricity consumption cost is \$194.9261 and the PAR is 1.2578. In addition, when the smart meter deploys the algorithm based on P-MCTS, the total electricity consumption cost is \$199.3983 and the PAR is 1.4326. The PAR values are calculated using the following formula,

$$PAR = \frac{H \max_h l_n^h}{\sum\limits_{n=1}^{N} \sum\limits_{a_n=1}^{A_n} E_{n,a_n}}. \tag{24}$$

Evidently, the differences between the algorithm based on BB and TS resultant costs and consumption schedules are negligible. Hence, for the proposed algorithm based on TS, we can claim that the optimal hourly scheduling with a minimum possible peak is achieved. In addition, the electricity consumption curve is more flattened and more evenly distributed over the day. In contrast, the algorithm based on P-MCTS does not result in the same minimal cost as the case of the algorithm based on TS, the PAR value is higher and the demand curve is not flatten. It can be said that the main objective of the proposed program is not fully achieved when using the algorithm based on P-MCTS.

The effectiveness of the algorithm based on TS method lies on the computational time savings compared to the algorithm based on BB and the algorithm based on P-MCTS. The computational time difference between the three algorithms does not vary much for small number of customers. However, the differences become in hundred multiples compared to the other two algorithms as the number of customers increases. Fig. 8 shows the computational time difference for different scenarios and for different number of customers.

In addition, as shown in Figures 9 and 10, the solution quality of the algorithm based on TS is very close to the algorithm based on BB as the total system cost and PAR values for different number of customers and scenarios are very similar. In contrast, the algorithm based on P-MCTS does not perform well as the number of customers increases. It can be stated that, with a lot of experiments and scenarios, the algorithm based on TS outperforms the algorithms based BB and P-MCTS in terms of efficiency.

In order to assess the system performance in case of violations, arbitrary 9 out of the 30 customers violate the assigned schedules with different loads at different times. Fig. 11 shows the impact of the violations on the assigned schedule provided to them. Obviously, all customers' bills payment are increased due to the increase in the total system load and hence the total system cost. Non-violators' bills are increased although they are committed to their assigned schedules, which in fact could have a negative impact on the level of contribution and involvement of customers on achieving the program objectives. The proposed fair billing mechanism ensures that all customers who abide to their assigned schedules do not get penalized or affected by others' violations as shown in Fig. 12. Furthermore, fairness among violators themselves is maintained as the penalty factor is proportional to the amount and time of the violation. For example, the penalty factor of customer 30 is the least among the violators as he/she violates the assigned schedules mainly during off-peak hours and in less total amount of electricity than all other customers. It can be stated that, with a lot of other experiments and scenarios, the proposed billing mechanism outperforms the billing mechanisms in the literature in terms of fairness in the case of customers' violations.

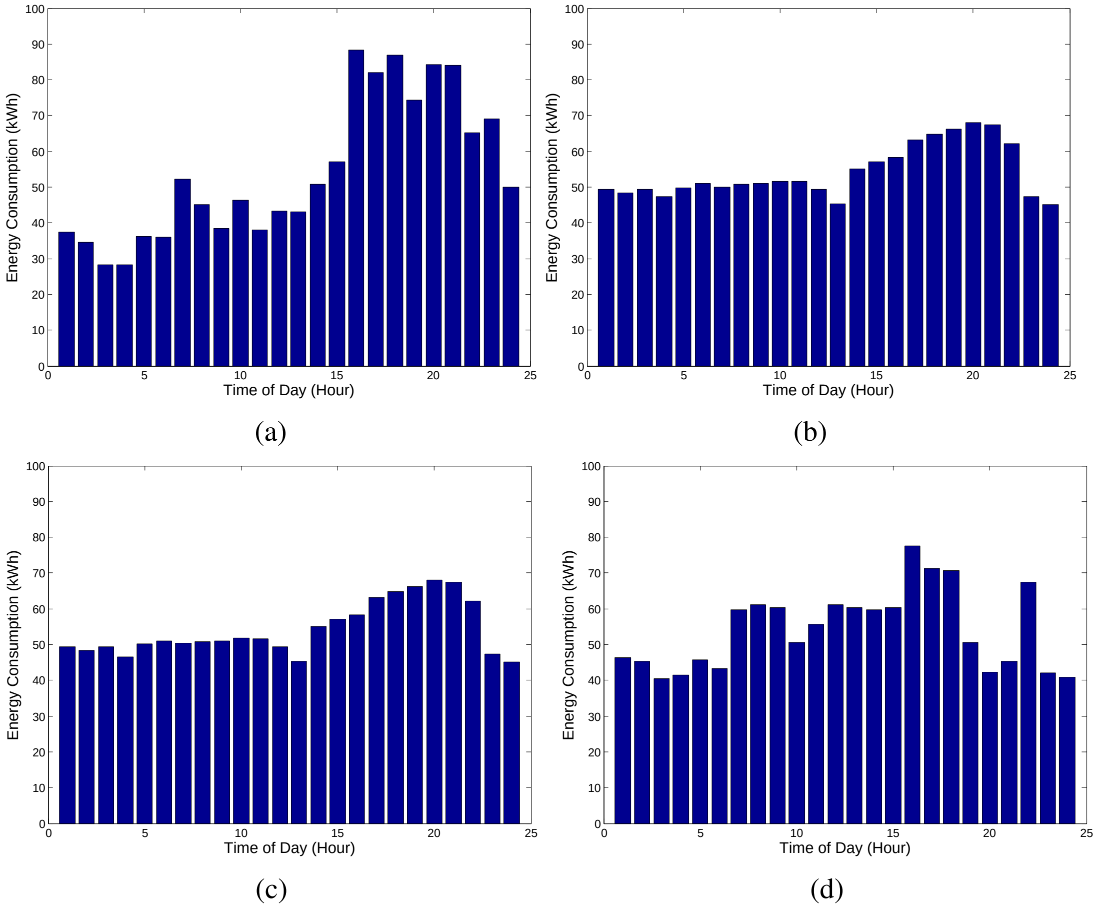
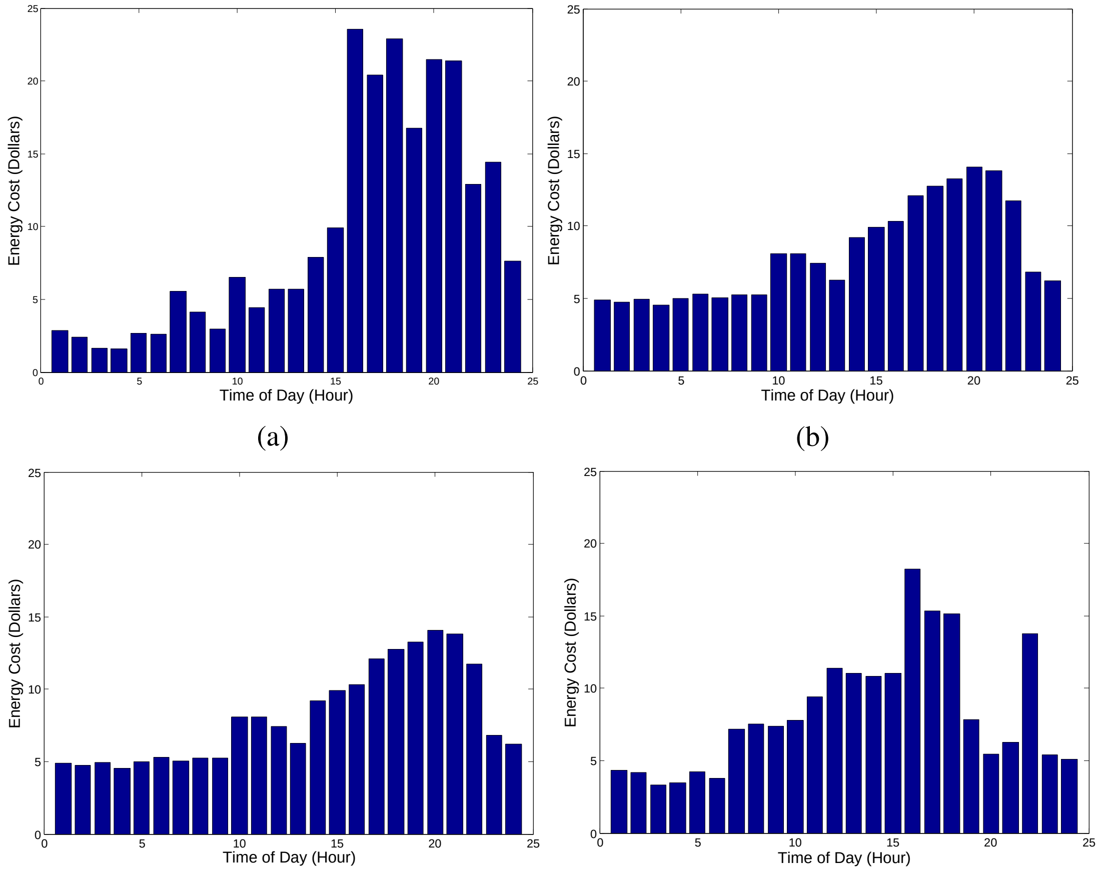


Figure 6: Energy consumption when (a) algorithm is not deployed in smart meter (b) algorithm based on TS is deployed in smart meter (c) algorithm based on BB is deployed in smart meter (d) algorithm based on P-MCTS is deployed in smart meter.



(a) (b) (c) (d)

Figure 7: Energy consumption cost when (a) algorithm is not deployed (b) algorithm based on TS is deployed in smart meter (c) algorithm based on BB is deployed in smart meter(d) algorithm based on P-MCTS is deployed in smart meter.

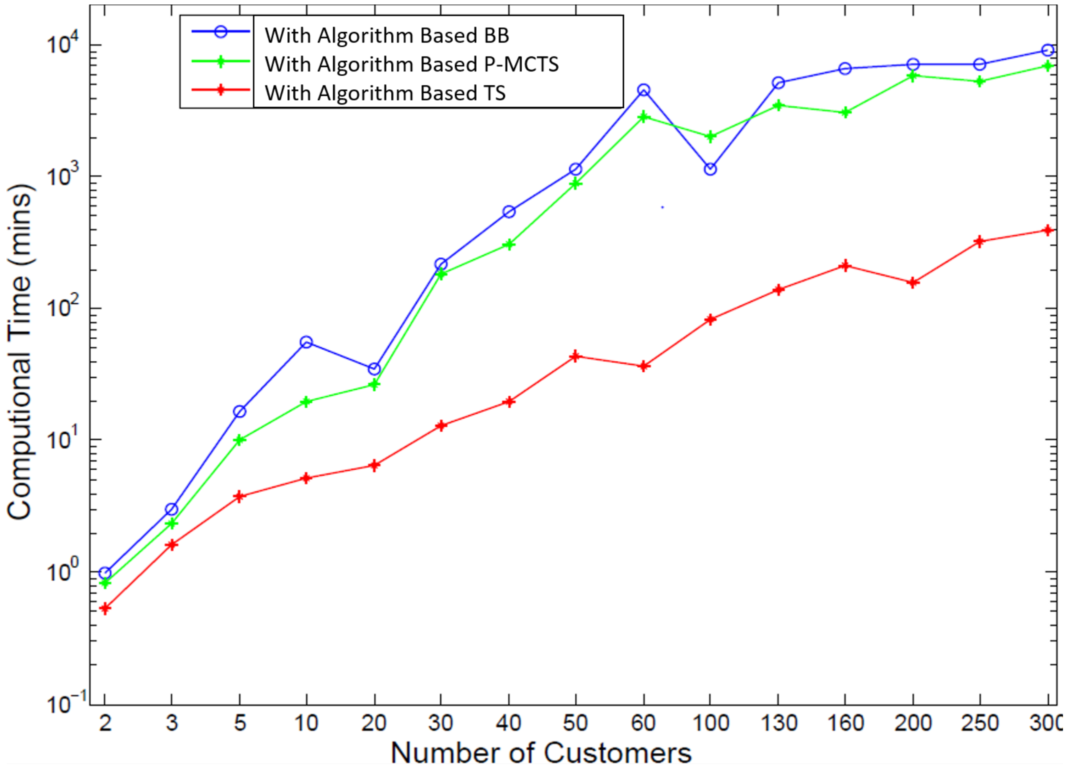


Figure 8: Computational time of the algorithm based on TS, algorithm based on BB and the algorithm based on P-MCTS.

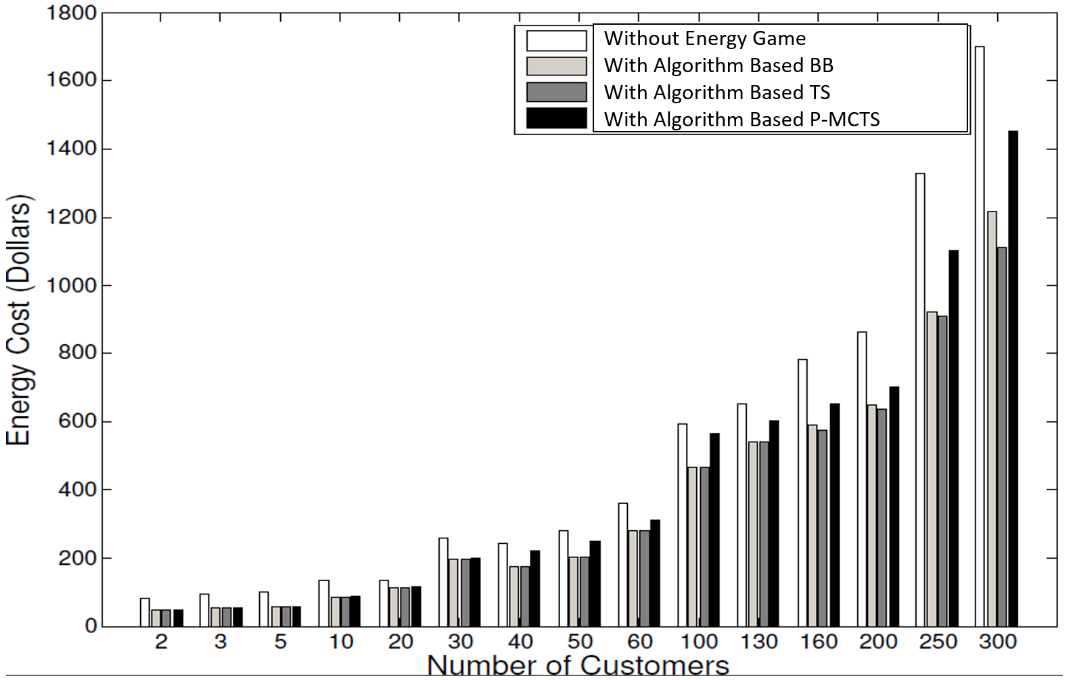


Figure 9: Total system cost comparison for different number of customers and scenarios.

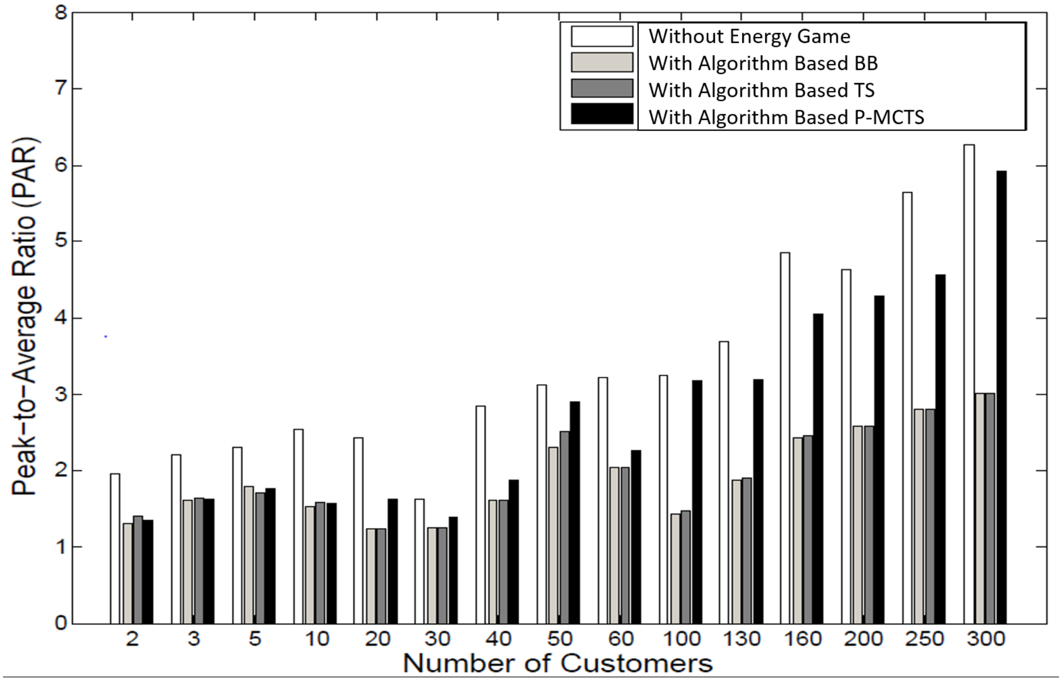


Figure 10: PAR for different number of customers and scenarios.

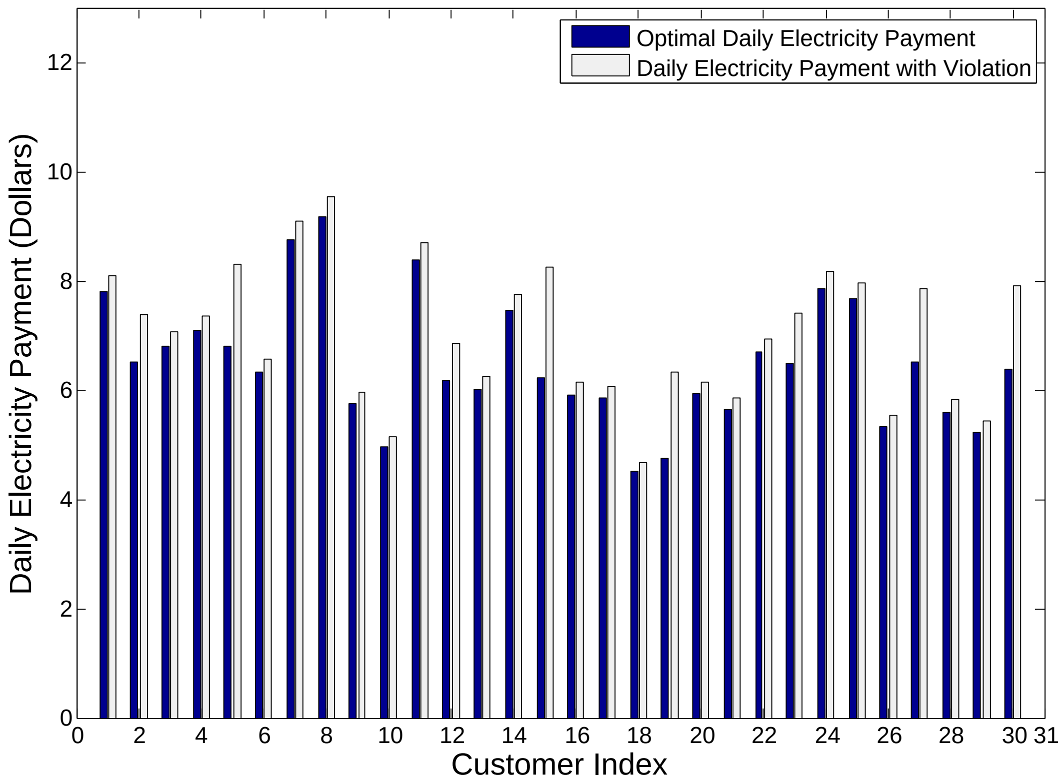


Figure 11: Customers' bills without applying violation penalty.

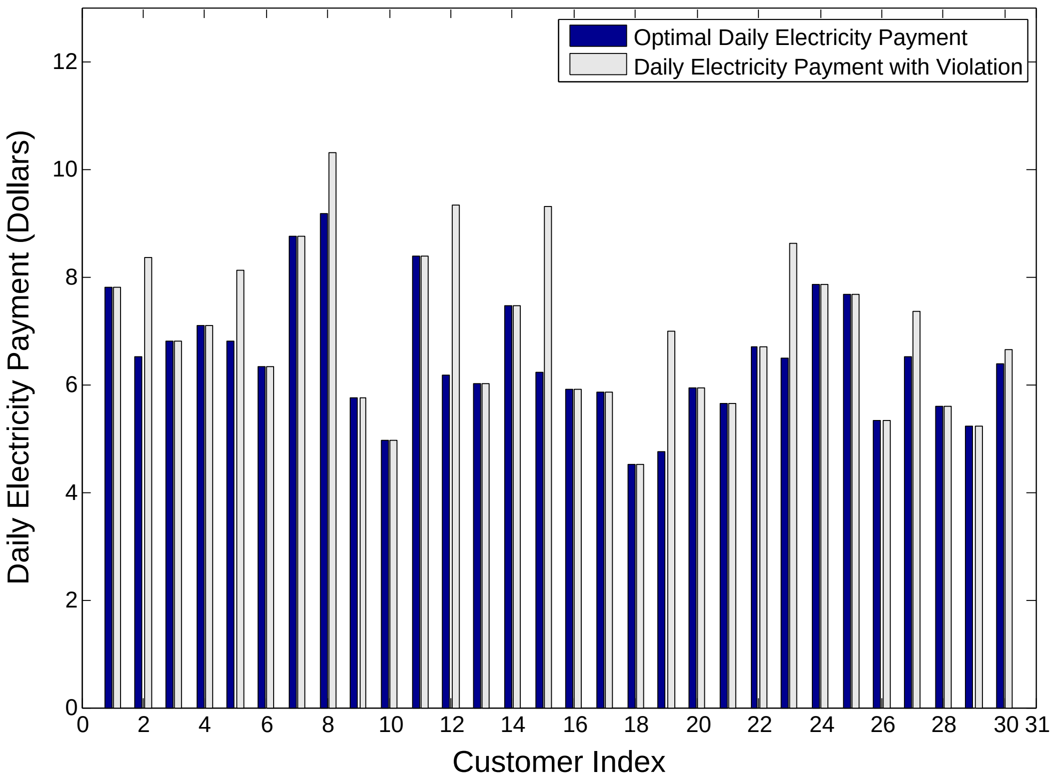


Figure 12: Customers' bills with applying violation penalty.

Chapter 4: Energy Consumption Scheduling for a Multi-Sources Multi-Customers (MSMC) System

4.1. Introduction

RESs, particularly wind and solar, are becoming significant power generation sources in the world. However, their intermittency and inherent stochastic nature result in huge fluctuations in the power generation, which jeopardize the balance between supply and demand. Besides the development of two-way communication and power infrastructures, and applying the concept of group ADSM, a microgrid is one of the very promising solutions proposed by the smart grid to support the integration of RESs and mitigate their intermittency nature. The concept of microgrid represents the envolvement from the current hierarchical distribution system toward a fully decentralized network [1]. The controlling, resource allocation, and monitoring of the grid elements can be better handled by the microgrid compared to the current grid due to the decentralization of geographical areas. Mainly, each microgrid consists of Distributed Energy Sources (DESs), DSEs, advanced communication infrastructure, Central Energy Management (CEM) unit, and a central energy source. DESs refer to small-scale power generators such as diesel generators, fuel cells, and RESs. Moreover, DESs can be either owned by individual customers (e.g., rooftop PV) or by the microgrid (e.g., PV farms). A major advantage of DESs is that it brings generated power closer to the point it is consumed, which may result in fewer thermal losses and a less stressed transmission network. DSEs charging and discharging capability is a practically appealing solution to smooth out the power fluctuations in DESs, thus improving both the reliability and efficiency of the microgrid. Batteries, flywheels, and pumped storage are examples of DSEs. The microgrid can operate in two modes: the grid-connected mode and the isolated mode [1]. Fig. 13 shows a typical topology of a microgrid.

In this chapter, an efficient and fair group ADSM program in the MSMC system, is proposed. The program aims at reducing the total system generation cost and increasing the penetration of RESs. First, the MSMC system model and residential load control, are illustrated. Then, the proposed energy consumption strategy which

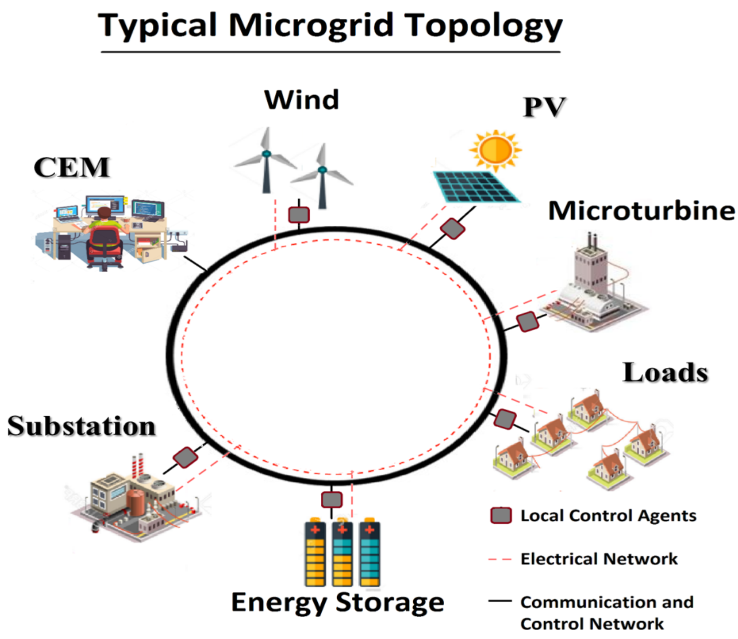


Figure 13: A typical microgrid topology

combines DEM and game-theoretic approaches, is presented. An energy consumption scheduling algorithm based on TS, is developed. Finally, numerical and simulation results for case studies are provided to demonstrate the effectiveness of the proposed program.

4.2. System Model

In this section, the analytical description of the MSMC system model is presented. Consider a MSMC system composed of a single fast-responding conventional generator shared by multiple customers in a microgrid, as shown in Fig. 14. The microgrid runs in the isolated operating mode, i.e., runs fully independently from the central grid. In order to be capable of trading energy among the different parties in the system and reliably implement the proposed group ADSM program, two-way flow of power and information networks are utilized. Each customer's household consists of a PV-based active generator, a smart meter and a set of shiftable and non-shiftable appliances, as shown in Fig. 15.

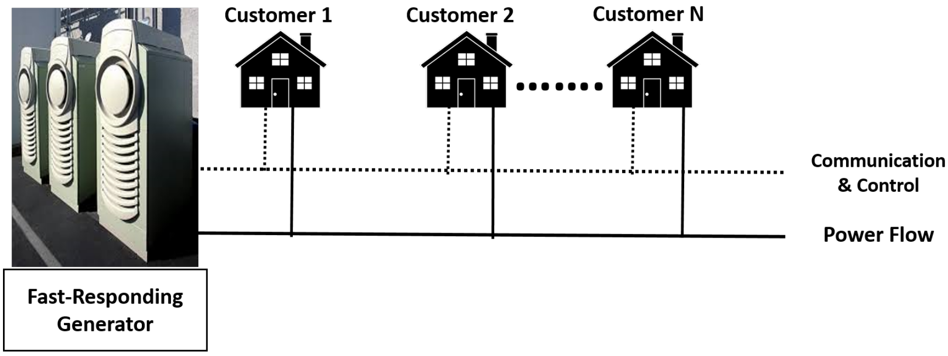


Figure 14: Block diagram of the MSMC system model.

The active generator is a combination of a rooftop PV panel and a storage device. As for the storage device, Lithium-ion batteries are chosen because of their low cost, high charge and discharge efficiencies, and their wide availability. They are used as energy storage units in the case of PV overproduction and as energy producers, otherwise. In this study, the harvested solar power via PV panels is assumed to be predicted 24-hours ahead according to the weather forecasting and the historic database of power generation. It should be noted that all customers have identical active generators specifications.

The smart meters and the sets of shiftable and non-shiftable appliances are previously detailed in Section 3.2.

Without loss of generality, it is assumed that each smart meter schedules the energy consumption for a period of a full day and night, $H = 24$, in advance, and time granularity of one hour. For each customer $n \in \mathcal{N}$, the energy load profile of all appliances $a_n \in \mathcal{A}_n$ in H time-slots is defined as

$$\mathfrak{X}_n = [\mathbf{x}_{n,1}, ..., \mathbf{x}_{n,A_n}] \in \mathbb{R}^{(H \times A_n)} \tag{25}$$

where the energy load profile by each appliance a_n is

$$\mathbf{x}_{n,a_n} = [x_{n,1}^{1}, ..., x_{n,a_n}^{H}]^T. \tag{26}$$

In this chapter, please note that the definition of a "day" means the periods from sunrise to sunset.

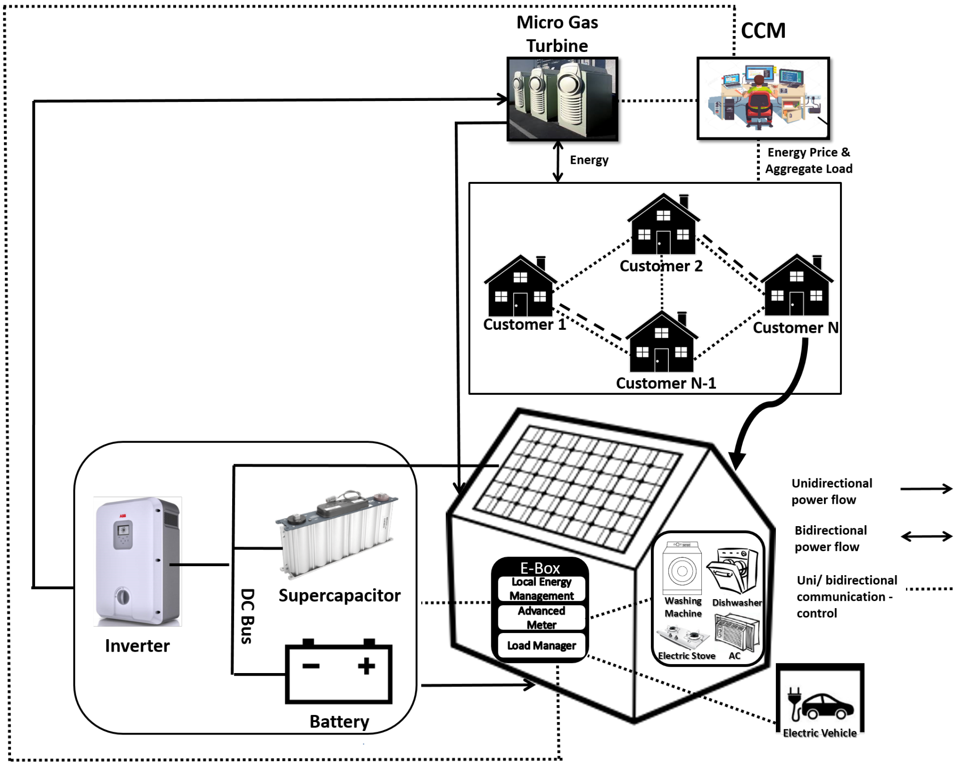


Figure 15: The MSMC system model.

The solar energy consumption by customer n for all appliances $a_n \in \mathcal{A}_n$ in H time-slots is

$$\mathfrak{Z}_n = [\mathbf{z}_{n,1}, ..., \mathbf{z}_{n,A_n}] \in \mathbb{R}^{(H \times A_n)} \tag{27}$$

where the solar energy consumption by each appliance a is

$$\mathbf{z}_{n,a_n} = [z^1_{n,a_n}, ..., z^H_{n,a_n}]^T. \tag{28}$$

The energy consumption from the conventional source for all appliances $a_n \in \mathcal{A}_n$ in H time-slots is defined as

$$\mathfrak{O}_n = [\mathbf{o}_{n,1}, ..., \mathbf{o}_{n,A_n}] \in \mathbb{R}^{(H \times A_n)} \tag{29}$$

where the energy consumption from the conventional source by each appliance a_n is

$$\mathbf{o}_{n,a_n} = [o^1_{n,a_n}, ..., o^H_{n,a_n}]^T. \tag{30}$$

The energy consumption from the battery stored energy for all appliances $a_n \in \mathcal{A}_n$ in H time-slots is as follows

$$\mathfrak{B}_n = [\mathbf{b}_{n,1}, ..., \mathbf{b}_{n,A_n}] \in \mathbb{R}^{(H \times A_n)} \tag{31}$$

where the energy consumption from the battery stored energy by each appliance a is

$$\mathbf{b}_{n,a_n} = [b^1_{n,a_n}, ..., b^H_{n,a_n}]^T. \tag{32}$$

The energy load profile in (25) can be rewritten as follows,

$$\mathfrak{X}_n = [\mathbf{x}_{n,1}, ..., \mathbf{x}_{n,A_n}] = \mathfrak{Z}_n + \mathfrak{O}_n + \mathfrak{B}_n, \tag{33}$$

where

$$\mathbf{x}_{n,a_n} = \mathbf{z}_{n,a_n} + \mathbf{o}_{n,a_n} + \mathbf{z}_{n,a_n}. \tag{34}$$

Please refer to Section 3.2 for the modeling of shiftable and non-shiftable appliances.

4.2.1. Fast-responding conventional generator. A fast-responding conventional generator shared by N customers is considered. The generator is only used to compensate for the mismatch between the load and solar energy supply. The generator is assumed to be a micro gas turbine.

In order to minimize the energy losses and air pollution at each start of the micro gas turbine, the gas turbine always works. Therefore, in the case of sufficient solar energy production, the turbine is forced to work with the lowest energy level $E_{G,min} = \frac{1}{2} E_{G,max}$,where $E_{G,max}$ is the generator rated energy [105].

4.2.2. Rooftop photovoltaic (PV) panel model. The PV power profile is foretasted 24-hours ahead using weather forecasting and historical database of PV power generation. The forecaster obtains power data each an hour, r^h_p. PV panels provide electrical power only during the day with a power peak around the midday. Moreover, it is assumed that the PV panels work with a Maximum Power Point Tracking (MPPT) algorithm [106].

For the solar energy generation estimation, let us define the initial time point as h_0 (start of the day) and the duration of the day as Δ_D. It should be noted that both parameters depend on the season and the weather conditions. The estimated solar energy production of the PV during each $h \in \mathcal{H}$ can be calculated from the PV power forecasting data, that is

$$r_e^h = \int_{h_0+\gamma_e t_e}^{h_0-(\gamma_e-1)t_e} r_p^h \, dh = t_e \, r_p^{h_0+\gamma_e t_e}, \tag{35}$$

where $\gamma_e \in \{0, 1, ..., 23\}$.

4.2.3. Storage model. In this work, it is assumed that all customers' storage batteries have identical practical constraints such as charging and discharging efficiency, leakage rate, capacity, and maximum charging rate [107]. In order to increase the lifetime of the battery and avoid deep charging, undercharging, and overcharging, a single charging and discharging cycle per day and night is considered.

For each customer n, the net storage vector for all time-slots $h \in \mathcal{H}$ is computed as

$$\mathbf{s}_n = \mathbf{s}_{n+} - \mathbf{s}_{n-}, \; \mathbf{s}_{n-}, \mathbf{s}_{n+} \geq 0, \forall h \in \mathcal{H}, \tag{36}$$

where $\mathbf{s}_n = [s_n^1, .., s_n^h, .., s_n^H]^T$, $\mathbf{s}_{n+} = [s_{n+}^1, .., s_{n+}^h, .., s_{n+}^H]^T$ is the energy charging profile, and $\mathbf{s}_{n-} = [s_{-n}^1, .., s_{n-}^h, .., s_{n-}^H]^T$ is the energy discharging profile.

Let $0 < \mu_+ \leq 1$ and $\mu_- \geq 1$ be, respectively, the charging and discharging efficiencies. The effective amount of stored energy depends on the battery efficiency, that is

- If s_{n+}^h is drawn from the PV panel to the battery, then only $s_{n+}^h \; \mu_+$ is effectively charged.
- If s_{n-}^h is required to be discharged from the battery, then $s_{n-}^h \; \mu_-$ should be discharged.

Moreover, the charge level of the battery at $h \in \mathcal{H}$ can be given as

$$q_n^h = \sigma q_n^{h-1} + \boldsymbol{\mu}^T \mathbf{S}_n^h, \; 0 < \sigma \leq 1, \tag{37}$$

where $\boldsymbol{\mu} = [\mu_+, \mu_-]^T$, $\mathbf{S}_n^h = [s_{n+}^h, s_{n-}^h]^T$, and σ is the battery leakage rate which is used to represent the decrease in the energy level over time. q_n^{h-1} is the charge level at the previous hour which is reduced by a factor of σ.

Furthermore, it is assumed that the final charge level q_n^H must be approximately the same as the initial charge level $q_n^{h_0}$, thus

$$|q_n^H - q_n^{h_0}| \leq \Theta,\ \Theta \geq 0, \tag{38}$$

where Θ is sufficiently small constant.

In addition, the stored energy level must be within an acceptable range, that is

$$-\sigma q_n^{h-1} \leq \boldsymbol{\mu}^T \mathbf{S}_n^h \leq c_n - \sigma q_n^{h-1}, h \in \mathcal{H}, \tag{39}$$

where c_n is the capacity of the battery.

Additionally, the maximum charging rate cannot be surpassed such that,

$$\boldsymbol{\mu}^T \mathbf{S}_n(h) \leq s_{max}. \tag{40}$$

In practice, there are other costs associated with batteries energy storage such as installment cost, operational cost, and aging cost that should be taken into account for the long-term battery management. For the purpose of simplicity, these factors are ignored in this study.

4.2.4. Energy generation cost model. At each time-slot $h \in \mathcal{H}$, the system total conventional energy that is required to be generated by the micro gas turbine is,

$$L_G^h = \sum_{n=1}^{N} \sum_{a_n=1}^{A_n} o_{n,a_n}^h, \forall h \in \mathcal{H} \tag{41}$$

The generation cost at each time-slot h can be approximated by a quadratic function, that is,

$$C(L^h) = \zeta^h (L_G^h)^2 + \varepsilon^h L_G^h + \upsilon^h, \tag{42}$$

where $\zeta^h(\text{cents/kW}) > 0$, $\varepsilon^h(\text{cents/kW})$, and $\upsilon^h(\text{cents/kW}) \geq 0$ are the fuel cost coefficients of the generator, at each hour $h \in \mathcal{H}$.

For each customer n, the solar power production cost is assumed to be negligible.

The energy selling price function by each customer n to the microgrid is defined as follows,

$$P^h_{\Omega_n} = \Phi^h(\Omega^h_n)^2, \ \Phi^h > 0, h \in \mathcal{H}, \tag{43}$$

where $\Omega^h_n \geq 0$ is the sold energy by customer n to the microgrid at $h \in \mathcal{H}$.

4.3. Residential Load Control

The main task of the smart meter in each customer's household is to determine the near-optimal energy consumption scheduling vector $\mathfrak{X}_n$. Let us identify the constraints and the feasible choices of the energy consumption scheduling vectors based on customers' preferences. Similar to the SSMC system, the constraints of the shiftable and non-shiftable appliances in (9), (10), (11), (12), (13), and (15) must be satisfied. It should be noted that the variables z^h_{n,a_n}, o^h_{n,a_n} and b^h_{n,a_n} combined have to satisfy the aforementioned constraints.

In addition to the previously mentioned constraints, (36-40) must be fulfilled to increase the battery lifetime and guarantee proper charging and discharging process. Also, the micro gas turbine has a minimum generation amount that must be used during all time-slots and is divided equally among the system customers, that is

$$E_{G_n,min} = \frac{E_{G,max}}{2N}, \ n \in \mathcal{N}. \tag{44}$$

Without loss of generality, it is assumed that any amount of power can be traded between the microgrid and the customers. In other words, any amount of power can be sold/bought by/to customers and the microgrid.

For each customer n, two power generation sources are considered: an active generator, and a micro gas turbine. As no solar power is available during the night, the energy consumption strategy is performed separately for the night and for the day.

Each customer is required to specify the most preferable consumption schedule $\mathfrak{X}_{n_p}$, which is not necessarily the optimal schedule,

$$\mathfrak{X}_{n_p} = [\mathbf{x}_{n_p,1}, ..., \mathbf{x}_{n_p,A_n}] \in \mathbb{R}^{(H \times A_n)}, \tag{45}$$

where the energy consumption profile for each appliance a is

$$\mathbf{x}_{n_p,a_n} = [x^1_{n_p,a_n}, ..., x^H_{n_p,a_n}]. \tag{46}$$

This schedule is fulfilled only by the predicted solar energy, stored battery energy, and minimum micro gas turbine energy. Any remaining energy is fulfilled by the turbine through the implementation of the game-theoretic approach, which is going to be explained later on. The benefit of allowing the customers to specify the most preferable schedule is to increase the comfortability level and motivate them to participate in the proposed group ADSM program.

4.4. Energy Consumption Scheduling Strategy

In this section, the proposed energy consumption scheduling strategy for the considered MSMC system, is explained. Each customer n schedules the energy consumption 24-hours ahead.

4.4.1. Energy consumption scheduling using deterministic energy management (DEM).

4.4.1.1. Energy consumption scheduling during the day. Due to the environmental and economical benefits of the utilization of RESs, the PV-based active generator is considered as the prior generation source, and the micro gas turbine is considered as the backup for the mismatch between the solar production and the load. For the day time $(h_0 < h < \Delta_D + h_0)$, all the available solar energy and minimum micro gas turbine energy are used to satisfy $\mathfrak{X}_{n_p}$. Any missing energy is satisfied using the turbine based on the proposed aggregative game, which will be explained later on. It should be noted that during the day period only one charging cycle is considered, i.e., no stored energy is used.

During $(h_0 < h < \Delta_D + h_0)$, two cases are considered,

- Case 1: If the available solar energy added to the minimum micro gas turbine energy is less than the customer's load, i.e.,

$$r_e^h + E_{G_n,min} < \sum_{a_n=1}^{A_n} x_{n_p,a_n}^h, n \in \mathcal{N}, h \in \mathcal{H}, \tag{47}$$

  then besides the use of the micro gas turbine minimum energy and available solar energy, the turbine has to generate the missing energy $E_{G_n}^h$, i.e.,

$$r_e^h + E_{G_n,min} + E_{G_n}^h = \sum_{a=1}^{A_n} x_{n_p,a_n}^h, \forall n \in \mathcal{N}, \forall h \in \mathcal{H}, \tag{48}$$

  where the conventional energy, $E_{G_n}^h$, is scheduled using the proposed aggregative game, which is going to be explained later on.

- Case 2: If the available solar energy added to the minimum micro gas turbine is more than the demand, i.e.,

$$r_e^h + E_{G_n,min} > \sum_{a_n=1}^{A_n} x_{n_p,a_n}^h, \forall n \in \mathcal{N}, \forall h \in \mathcal{H}, \tag{49}$$

  then the solar energy and the minimum micro gas turbine energy are completely used. The excess solar energy will be stored in the battery if the charge level, charging rate, and all other constraints in (36-40) are satisfied. If any of the constraints is violated, then the excess energy will be traded with the microgrid at the price of $P_{\Omega_n}^h$.

Clearly, it is not practical to account only for the total energy per time-slot without considering the different types of the appliances. Algorithm 5 represents the proposed methodology of how to deal with the shiftable and non-shiftable appliances during the day period. The priority is always given to supply the non-shiftable appliances using the available solar and minimum micro gas turbine energy. The number of completely or partially supplied non-shiftable appliances is denoted as $\hat{A_{n_s}}$. Then, if excess energy is still available, the adjustable appliances are supplied. The number of completely or partially supplied appliances is denoted as $\hat{A_{n_d}}$. If extra amount of energy is still available, then it is used for the time-shiftable appliances. Due to the continuous operating constraint of time-shiftable appliances, each time-shiftable appliance has to be fully supplied. If the extra energy is not enough for fully supplying a time-shiftable appliance, $\overline{a}_{n_t}$, then the energy is either stored or sold to the microgrid based on the system constraints and energy price. The number of completely supplied appliances is denoted as $\hat{A_{n_t}}$.

4.4.1.2. Energy consumption scheduling during the night. During the night time, for each $h \in \mathcal{H}$, two sources of energy are considered: the storage device in the active generator, and the micro gas turbine. The prior source of energy is considered to be the storage device. There are two cases that could happen during the night. For both cases, the storage device has to be discharged and reach the minimum charge level in order to be ready for the charging in the next day.

- Case 1: If the available stored energy and the minimum micro gas turbine energy are more than the customers' load, i.e.,

$$q_n^h + E_{G_n,min} > \sum_{a_n=1}^{A_n} x_{n_p,a_n}^h, \forall n \in \mathcal{N}, \forall h \in \mathcal{H}, \tag{50}$$

  then, the priority is given to the stored energy and minimum turbine energy to be used. The remaining amount of energy is sold to the microgrid at the price of $P_{\Omega_n}^h$. This case can be represented as,

$$q_n^h + E_{G_n,min} - E_{G_n}^h = \sum_{a_n=1}^{A_n} x_{n_p,a_n}^h, \forall n \in \mathcal{N}, \forall h \in \mathcal{H}. \tag{51}$$

- Case 2: If the available stored energy and the minimum gas turbine energy are less than the customers' demand, i.e.,

$$q_n^h + E_{G_n,min} < \sum_{a_n=1}^{A_n} x_{n_p,a_n}^h, \forall n \in \mathcal{N}, \forall h \in \mathcal{H}, \tag{52}$$

Algorithm 5 Energy Consumption Scheduling During Day Time: Executed by each customer $n \in \mathcal{N}$.

for $h = h_0 : 1 : \Delta_D + h_0$ **do**
  if $r_e^h + E_{G_n,min} > 0$ **then**
    $\sum_{a_{n_s}=1}^{\hat{A_{n_s}}} x_{n_p,a_{n_s}}^h \leftarrow r_e^h + E_{G_n,min}$
  else
    Break.
  end if
  if $r_e^h + E_{G_n,min} - \sum_{a_{n_s}=1}^{\hat{A_{n_s}}} x_{n_p,a_{n_s}}^h > 0$ **then**
    $\sum_{a_{n_d}=1}^{A_{\hat{a_{n_d}}}} x_{n_p,a_{n_d}}^h \leftarrow r_e^h + E_{G_n,min} - \sum_{a_{n_s}=1}^{\hat{A_{n_s}}} x_{n_p,a_{n_s}}^h$
  else
    Break.
  end if
  Let $\overline{a}_{n_t} = 0$
  for $a_{n_t} = 1 : 1 : A_{n_t}$ **do**
    if $r_e^h + E_{G_n,min} - \sum_{a_{n_s}=1}^{\hat{A_{n_s}}} x_{n_p,A_{n_s}}^h - \sum_{a_{n_d}=1}^{\hat{A_{n_d}}} x_{n_p,a_{n_d}}^h - \overline{a}_{n_t} \geq x_{n_p,a_{n_t}}^h$ **then**
      $x_{n_p,a_{n_t}}^h \leftarrow r_e^h + E_{G_n,min} - \sum_{a_{n_s}=1}^{\hat{A_{n_s}}} x_{n_p,a_{n_s}}^h - \sum_{a_{n_d}=1}^{\hat{A_{n_d}}} x_{n_p,a_{n_d}}^h - \overline{a}_{n_t}$,
      $\overline{a}_{n_t} = \overline{a}_{n_t} + x_{n_p,a_{n_t}}^h$
    else
      Break.
    end if
  end for
  if $r_e^h + E_{G_n,min} - \sum_{a_{n_s}=1}^{\hat{a_{n_s}}} x_{n_p,a_{n_s}}^h - \sum_{a_{n_s}=1}^{\hat{A_{n_s}}} x_{n_p,a_{n_d}}^h - \sum_{a_{n_t}=1}^{\hat{A_{n_t}}} x_{n_p,a_{n_t}}^h > 0$ **then**
    if (36 - 40) are satisfied **then**
      $q_n^h \leftarrow r_e^h + E_{G_n,min} - \sum_{a_{n_s}=1}^{\hat{A_{n_s}}} x_{n_p,a_{n_s}}^h - \sum_{a_{n_d}=1}^{\hat{A_{n_d}}} x_{n_p,a_{n_d}}^h - \sum_{a_{n_t}=1}^{\hat{A_{n_t}}} x_{n_p,a_{n_t}}^h$
    else
      Sell to microgrid at price of $P_{\Omega_n}^h$.
    end if
    Break.
  end if
  if $r_e^h + E_{G_n,min} < \sum_{a_n=1}^{A_n} x_{n_p,a_n}^h$ **then**
    $r_e^h + E_{G_n,min} - \sum_{a_n=1}^{A_n} x_{n_p,a_n}^h = E_{G_n}^h$ & Apply Mechanism in 4.4.2.
  else
    Break.
  end if
end for

then, all the available stored energy and minimum gas turbine energy are used. The turbine must substitute for the missing energy, that is,

$$q_n^h + E_{G_n,min} + E_{G_n}^h = \sum_{a_n=1}^{A_n} x_{n_p,a_n}^h, \forall n \in \mathcal{N}, \forall h \in \mathcal{H}. \tag{53}$$

Algorithm 6 Energy Consumption Scheduling During Night Time: Executed by each customer $n \in \mathcal{N}$.

for $h = h_0 + \Delta_D : 1 : h_0$ **do**
  if $q_n^h + E_{G_n,min} > 0$ **then**
    $\sum_{a_n=1}^{\hat{A_{n_s}}} x_{n_p,a_{n_s}}^h \leftarrow q_n^h + E_{G_n,min}$
  else
    Break.
  end if
  if $q_n^h + E_{G_n,min} - \sum_{a_{n_s}=1}^{\hat{A_{n_s}}} x_{n_p,a_{n_s}}^h > 0$ **then**
    $\sum_{a_{n_d}=1}^{\hat{A_{n_s}}} x_{n_p,a_{n_d}}^h \leftarrow q_n^h + E_{G_n,min} - \sum_{a_{n_s}=1}^{\hat{A_{n_s}}} x_{n_p,a_{n_s}}^h$
  else
    Break.
  end if
  Let $\overline{a}_{n_t} = 0$
  for $a_{n_t} = 1 : 1 : A_{n_t}$ **do**
    if $q_n^h + E_{G_n,min} - \sum_{a_{n_s}=1}^{\hat{A_{n_s}}} x_{n_p,a_{n_s}}^h - \sum_{a_{n_d}=1}^{\hat{A_{n_d}}} x_{n_p,a_{n_d}}^h - \overline{a}_{n_t} \geq x_{n_p,a_{n_t}}^h$ **then**
      $x_{n_p,a_{n_t}}^h \leftarrow q_n^h + E_{G_n,min} - \sum_{a_{n_s}=1}^{\hat{A_{n_s}}} x_{n_p,a_{n_s}}^h - \sum_{a_{n_d}=1}^{\hat{A_{n_d}}} x_{n_p,a_{n_d}}^h - \overline{a}_{n_t}$,
      $\overline{a}_{n_t} = \overline{a}_{n_t} + x_{n_p,a_{n_t}}^h$
    else
      Break.
    end if
  end for
  if $q_n^h + E_{G_n,min} - \sum_{a_{n_s}=1}^{\hat{A_{n_s}}} x_{n_p,a_{n_s}}^h - \sum_{a_{n_d}=1}^{\hat{A_{n_d}}} x_{n_p,a_{n_d}}^h - \sum_{a_{n_t}=1}^{\hat{A_{n_t}}} x_{n_p,a_{n_t}}^h > 0$ **then**
    Sell to microgrid at price of $P_{\Omega_n}^h$.
  else
    Break.
  end if
  if $q_n^h + E_{G_n,min} < \sum_{a=1}^{A} x_{n_p,a_n}^h$ **then**
    $q_n^h + E_{G_n,min} + E_{G_n}^h = \sum_{a_n=1}^{A_n} x_{n_p,a_n}^h$ & Apply Mechanism in 4.4.2.
  else
    Break.
  end if
end for

The conventional energy, $E_{G_n}^h$, is scheduled using the proposed aggregative game, which is going to be explained later on. Similar to the methodology used during the day for the scheduling of the different types of appliances, Algorithm 6 shows the proposed mechanism during the night.

4.4.2. Energy consumption aggregative game formulation. As previously mentioned, the conventional energy generated, $E^h_{G_n}$, by the micro gas turbine due to shortage in solar energy supply is scheduled such that the total system cost is reduced. In this subsection, an aggregative energy consumption game to model the strategic behavior of the customers in the MSMC, is investigated. All customers are assumed to be selfish as they need to minimize their individual energy bills through the scheduling of a day-ahead energy consumption.

First, once the hourly available solar energy and minimum micro gas turbine are used, the schedule $\mathfrak{X}_{n_p}$ is discarded. The remaining amount of energy needed by customer n, $E^h_{G_n}$, is scheduled using the following aggregative game mechanism.

As discussed in Section 3.5, the game is formulated naturally based on the fact that each customer's bill is affected not only by the customer's consumption alone but rather by the aggregated consumption of all other customers as well. In other words, the total conventional energy generation cost is shared among customers based on their portions of the load. The aggregative game is identified as follows:

- Players: customers in set $\mathcal{N}$.
- Strategies: each customer n selects the consumption profile $\mathfrak{O}_n$ that maximizes the payoffs and satisfies all the constraints.
- Payoffs: for each customer n, the payoff function is $-b^*_{n,o}$, where $b^*_{n,o}$ is the near-optimal total electricity bill.

The billing mechanism is as follows,

$$b^*_{n,o} = \psi_{n,o} \min_{\mathfrak{O}_n} \sum_{h}^{H} C\left(\sum_{a_o}^{A_{no}} o^h_{n,a_o} + {O_m}^h\right), \tag{54}$$

where $\mathcal{A}_o = \mathcal{A}_n \backslash \{\hat{A_{n_s}}, \hat{A_{n_t}}, \hat{A_{n_d}}\}$, $\psi_{n,o} = \frac{\sum_{h=1}^{H} E^h_{G_n}}{\sum_{h=1}^{H} \sum_{m=1, m\neq n}^{N} E^h_{G_m}}$, and ${O_m}^h$ is the total load of all system customers except the n^{th} customer at $h \in \mathcal{H}$.

4.5. Energy Consumption Scheduling Algorithm Based on Tabu Search (TS)

For a more efficient implementation of the energy consumption scheduling strategy, the energy consumption scheduling algorithm based on TS in Section 3.6 is implemented. Please refer to Section 3.6 for the explanation of the proposed TS based algorithm.

4.6. Total Energy Consumption Bill

For each customer n, the total energy consumption bill is defined as the conventional energy (from the micro gas turbine) price minus the sold energy price, that is,

$$b_{n,o} = \sum_{h=1}^{H} \left(b_{n,o}^{h} - P_{\Omega_n}^{h}\right), n \in \mathcal{N}, b_n \geq 0, \tag{55}$$

where $b_{n,o}^{h} = b_{n,o}^{h*} + P_v^h(C(L_G^h) - C(L_G^{h*}))$, $b_{n,o}^{h*}$ is the hourly near-optimal bill, $C(L_G^h)$ is the actual total system energy cost and $C(L_G^{h*})$ is the total near-optimal system energy cost at $h \in \mathcal{H}$.

It should be noted that the bill in (55) is calculated based on the true measured amount of solar power generated not the predicted.

4.7. Simulation Results

4.7.1. Scenario setup.

In this section, simulation results are presented in order to evaluate the performance of the proposed group ADSM program in the MSMC system. In the considered system, we have 30 customers ($N = 30$) scheduling their energy consumption for the next 24 hours. For the purpose of comparison between the proposed mechanisms in SSMC and MSMC systems, the same scenario setup is used as presented in Section 3.7.1. The random generated schedules in Section 3.7.1 (when smart meters do not deploy an energy consumption scheduling algorithm) are considered as the preferable schedules $\mathfrak{X}_{n_p}$, $n \in \mathcal{N}$. As for the micro gas turbine, the rated energy is $E_{G,max} = 33$ kWh. In consequence, by using (44), 0.55 kWh is allocated for each customer at all time-slots $h \in \mathcal{H}$. All customers have identical smart meters capabilities and active generator specifications. In order to increase the lifetime of the battery and avoid deep charging, undercharging, and overcharging, a single charging and discharging cycle per day and night is considered. Each customer's battery capacity is $c_n = 4$kWh. The charging and discharging efficiencies are assumed to be $\mu_+ = 0.9$, $\mu_- = 1.1$, respectively. The maximum charging rate, $s_{max} = 0.125c_n \backslash h$. Moreover, the initial charge level is assumed to be $q_n^{h_0} = 0.25\ c_n$ and $\Theta = 0$. The leakage rate is $\sigma = \sqrt[24]{0.9}$ [107]. Moreover, 3kW rooftop PV panels are utilized. The hourly predicted solar energy generation over one day period is taken from [105]. Fig. 16 shows the hourly predicted solar energy and the minimum allocated micro gas turbine energy for each customer n. The micro gas turbine energy generation cost function is assumed to be as in (42). The parameters values are $\zeta^h 0.3$, $\varepsilon^h = 0.2$ and $\upsilon^h = 0.08$ cents during daytime hours (8:00 am to midnight) and $\zeta^h = 0.2$, $\varepsilon^h = 0.1$ and $\upsilon^h = 0.05$ cents during night hours (midnight to 8:00 am). Moreover, the billing system is assumed to be budget balanced, i.e, the total system cost is equal to the total bills of all customers. The energy selling price function by each customer n to the microgrid is as in (43), where $\Phi^h = 0.5$ cents during daytime hours (8:00 am to midnight), and $\Phi^h = 0.4$ cents during during night hours (midnight to 8:00 am).

4.7.2. Results and discussion. Now, the proposed energy consumption strategy in Section 4.4 is implemented as follows. First, the proposed DEM mechanism is applied on the preferable schedules $\mathfrak{X}_{n_p}$ (discussed in Section 3.7.1). The amount of the total allocated energy from the PV panel and the minimum micro gas turbine energy to each customer n, which must be fully used, is shown in Fig. 17. Figures. 18 and 19 show, respectively, the total hourly preferable energy consumption $\mathcal{X}_{n_p}$ and the associated cost, for the 30 customers during a day. By following the procedure in algorithms 5 and 6, the total system charged/discharged energy to/from the batteries, and the total system sold energy to the microgrid, are as presented in Figures 20,and 21, respectively.

Now, in order to reduce the micro gas turbine energy generation cost of the remaining energy that is not satisfied by the solar energy and minimum turbine energy, the proposed algorithm based on TS is deployed in the smart meters. For the purpose of

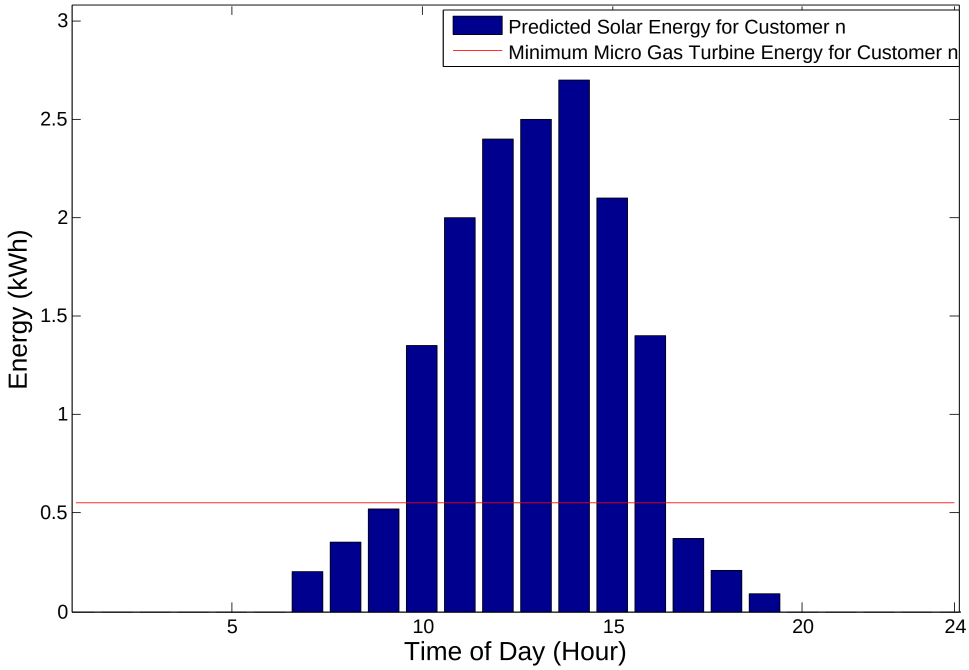


Figure 16: The hourly predicted solar energy and the minimum micro gas turbine energy for each customer n during a day.

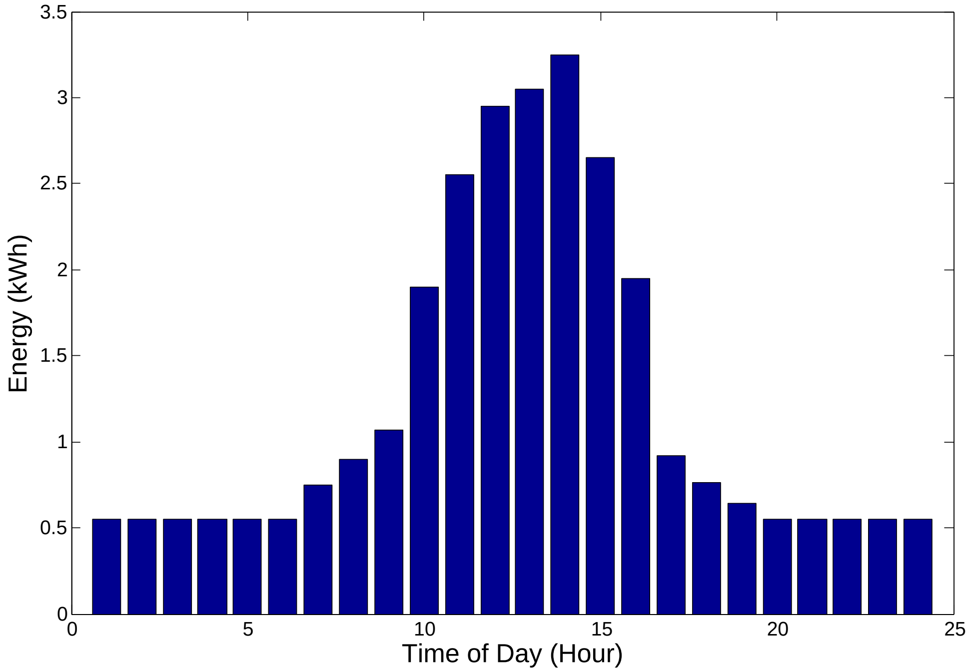


Figure 17: The total hourly allocated energy from the PV panel and the minimum micro gas turbine energy for each customer n during a day.

comparison with the algorithms based BB and P-MCTS, they are also deployed in the smart meters. As for the P-MCTS method, the algorithm is run as proposed in [87]. In order to make a fair comparison between the three algorithms, the initial guess is uni-

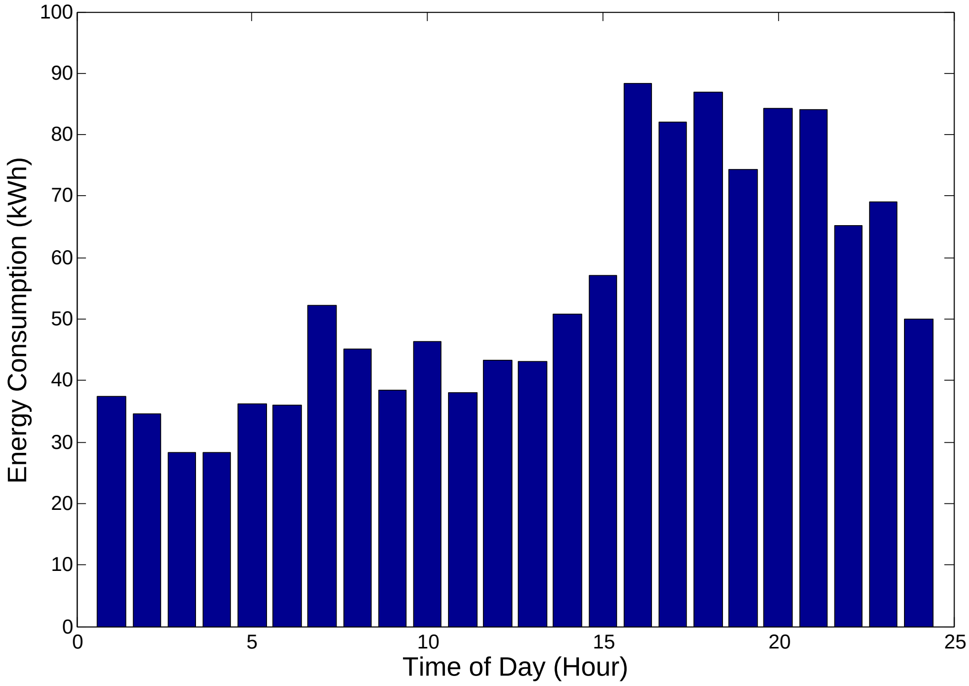


Figure 18: The total system hourly preferable energy consumption $\mathcal{X}_{n_p}$ during a day.

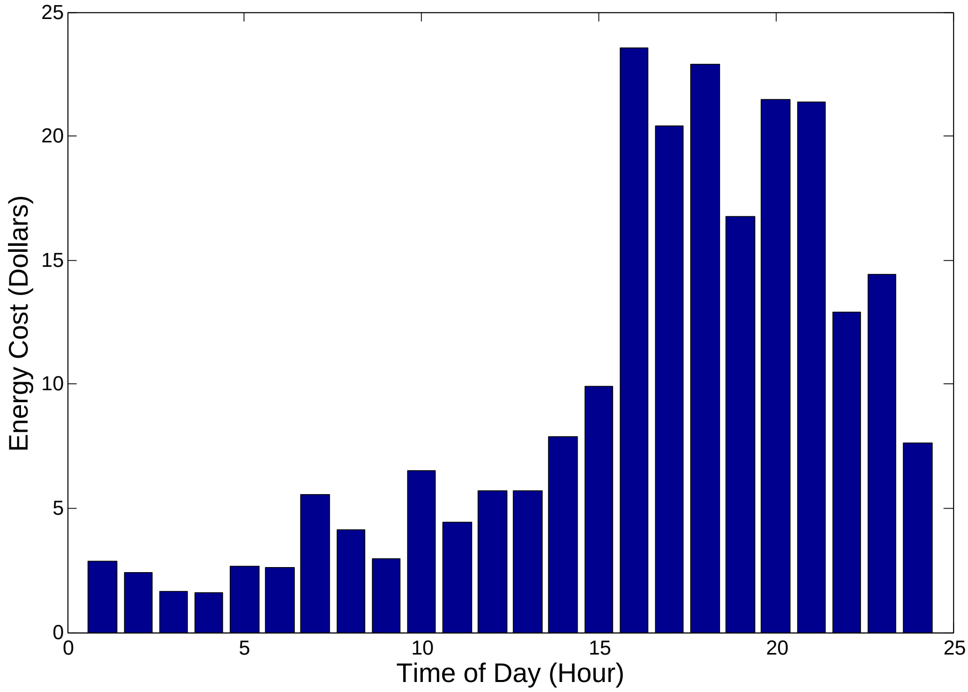


Figure 19: The total system hourly preferable energy consumption cost during a day.

fied. As mentioned in Section 3.6, the initial guess is formalized through the relaxation of the integer constraints and variables in (54) such it can be solved using IPM. The three methods are compared in terms of their computational time and results quality. In

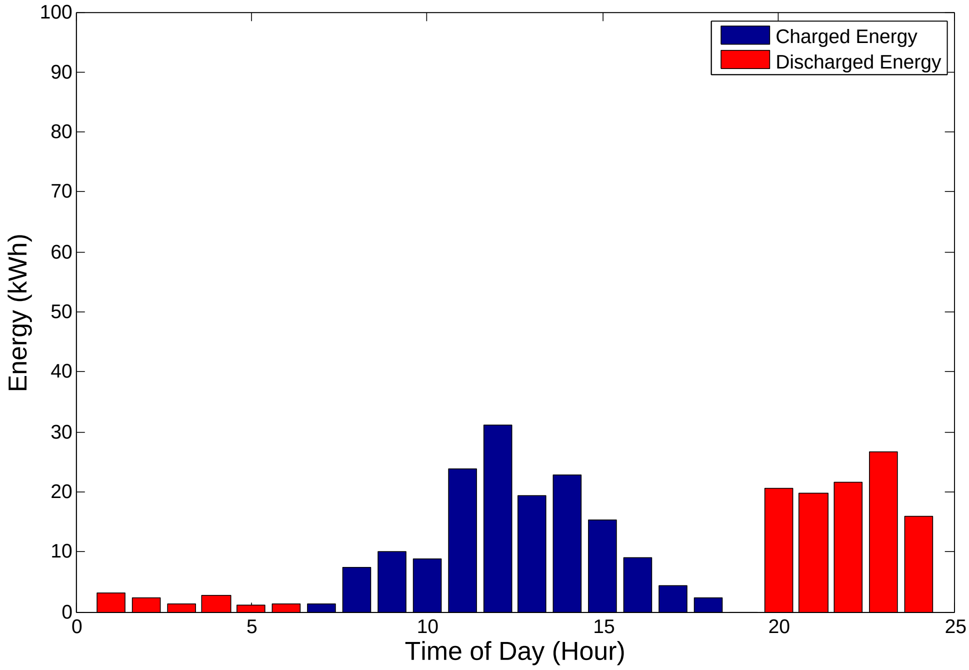


Figure 20: The total system hourly charged/discharged energy from/to batteries during a day.

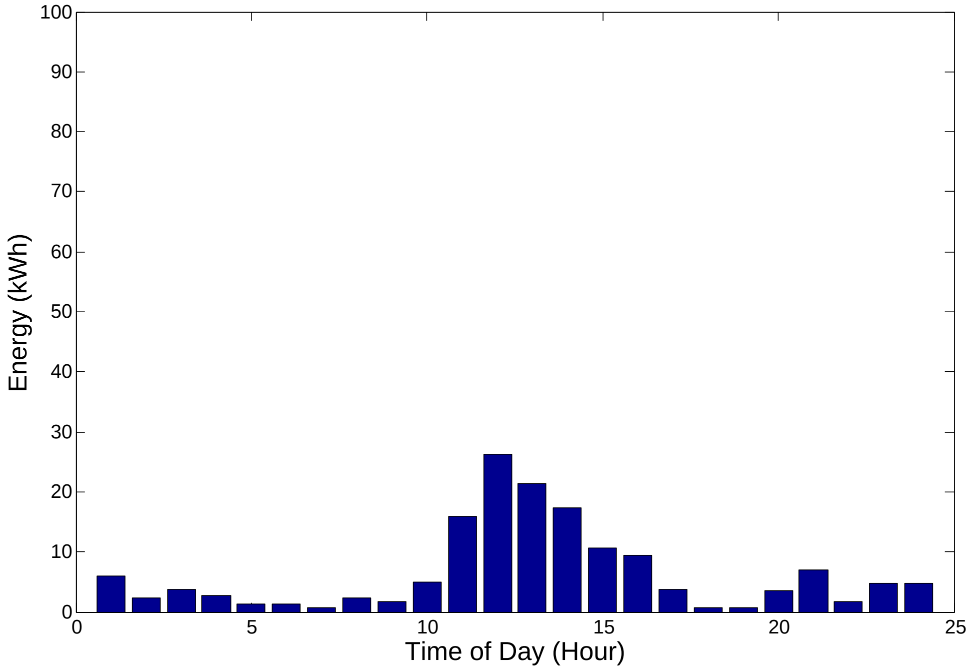


Figure 21: The total system hourly sold energy to the microgrid during a day.

addition, the performance of both the SSMC and MSMC systems is compared in terms of the total systems cost.

Figures 22 and 23 show the total amount of energy that is not satisfied by the solar energy and minimum micro gas turbine energy after implementing the DEM mechanism, and the associated cost, respectively, for the cases when customer's n smart meter does not deploy an energy consumption scheduling algorithm, runs the algorithm based on TS, runs the algorithm based on BB, and runs the algorithm based on P-MCTS. All system constraints are fulfilled for the cases when the three algorithms are run in the smart meters. Clearly, both algorithms based BB and TS have almost have converged to the same results, hence the convergence of the algorithm based on TS is achieved. As for the algorithm based on P-MCTS, the result is not as accurate as the algorithm based on TS, hence its convergence is not achieved.

As shown in Fig. 23 when the smart meter does not deploy an energy consumption scheduling algorithm, the PAR is 2.1136 and the total electricity consumption cost is \$130.2404. Moreover, when the algorithm based on TS is deployed in the smart meter, the total electricity consumption cost is \$102.3543 and the PAR is 1.3657. For the case when the smart meter deploys the algorithm based on BB, the total electricity consumption cost is \$102.3004 and the PAR is 1.3657. In addition, when the smart meter deploys the algorithm based on P-MCTS, the total electricity consumption cost is \$106.1097 and the PAR is 1.6275.

Evidently, the differences between the algorithm based on BB and TS resultant costs and consumption schedules are negligible. In addition, the electricity consumption curve is more flattened and more evenly distributed over the day. Hence, for the proposed algorithm based on TS, we can claim that the optimal hourly scheduling with a minimum possible peak is achieved. In contrast, the algorithm based on P-MCTS does not result in the same minimal cost as the case of the algorithm based on TS, the PAR value is higher and the demand curve is not flatten. It can be said that the main objective of the proposed program is not fully achieved when using the algorithm based on P-MCTS.

The effectiveness of the algorithm based on TS method lies on the computational time savings compared to the algorithm based on BB and the algorithm based on P-MCTS. The computational time difference between the three algorithms does not vary much for small number of customers. However, the differences become in hundred multiples compared to the other two algorithms as the number of customers increases. Fig. 24 shows the computational time difference for different scenarios and for different number of customers.

In addition, as shown in Fig. 25, the solution quality of the algorithm based on TS is very close to the algorithm based on BB as the total system cost for different number of customers and scenarios are very similar. In contrast, the algorithm based on P-MCTS does not perform well as the number of customers increases. It can be stated that, with a lot of experiments and scenarios, the algorithm based on TS outperforms the algorithms based BB and P-MCTS in terms of efficiency.

Fig. 26 shows the total SSMC and MSMC systems cost percentage difference for identical scenarios. The scenarios are as discussed in this Section and Section 3.7.1. Clearly, always the total MSMC system cost for a scenario is higher than the cost of the SSMC system. This is a result of fully using the solar energy and selling excess energy based on the proposed program to the microgrid by the MSMC system customers.

In order to assess the system performance in case of violations, arbitrary 9 out of the 30 customers violate the assigned schedules with different loads at different times. It should be noted that the total bill amount for a customer n is as presented (55). Fig. 27 shows the impact of the violations on the assigned schedule provided to them. Obviously, all customers' bills payment are increased due to the increase in the total system load and hence the total system cost. Non-violators' bills are increased although they are committed to their assigned schedules, which in fact could have a negative impact on the level of contribution and involvement of customers on achieving the program objective, i.e., minimizing the total system cost. The proposed fair billing mechanism ensures that all customers who abide to their assigned schedules do not get penalized or affected by others' violations as shown in Fig. 28. Furthermore, fairness among violators themselves is maintained as the penalty factor is proportional to the amount and time of the violation. For example, the penalty factor of customer 5 is the least among the violators as he/she violates the optimal schedules mainly during off-peak hours and in less total amount of electricity than all other customers. It can be stated that, with a lot of other experiments and scenarios, the proposed billing mechanism outperforms the billing mechanisms in the literature in terms of fairness in the case of customers' violations.

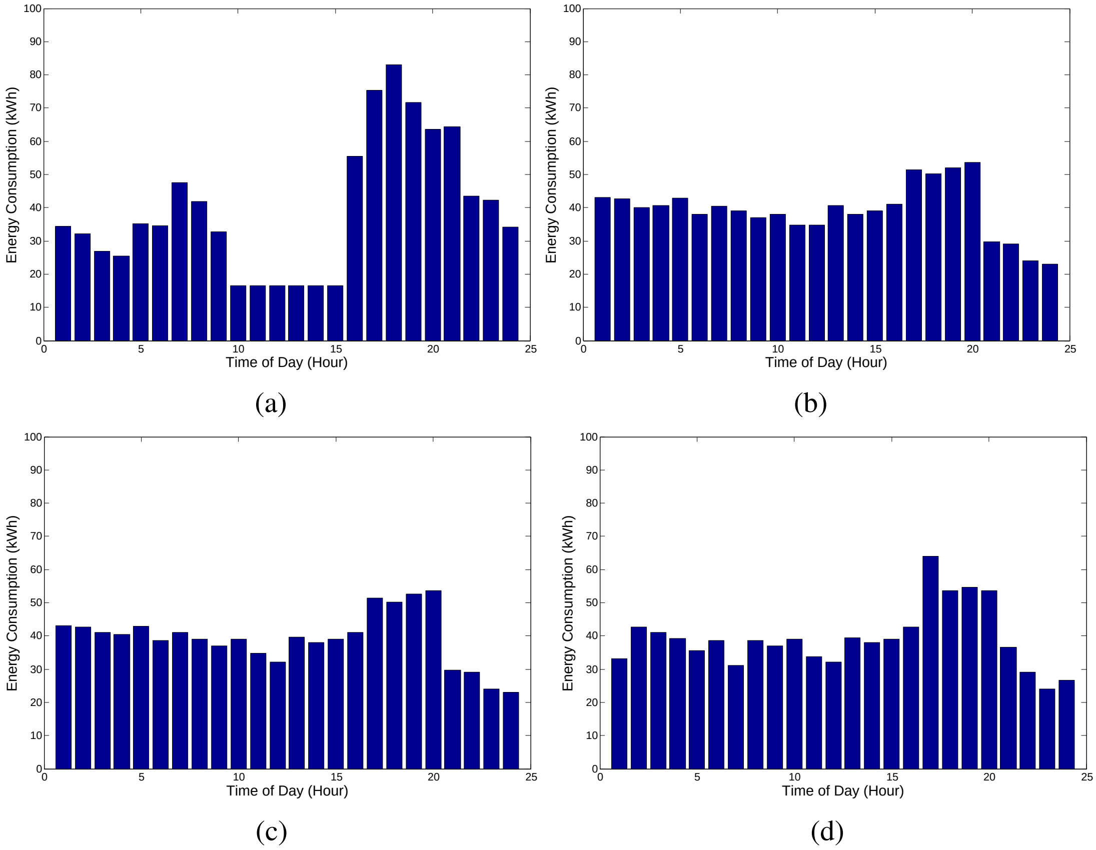


Figure 22: Energy consumption when (a) algorithm is not deployed in smart meter (b) algorithm based on TS is deployed in smart meter (c) algorithm based on BB is deployed in smart meter (d) algorithm based on P-MCTS is deployed in smart meter.

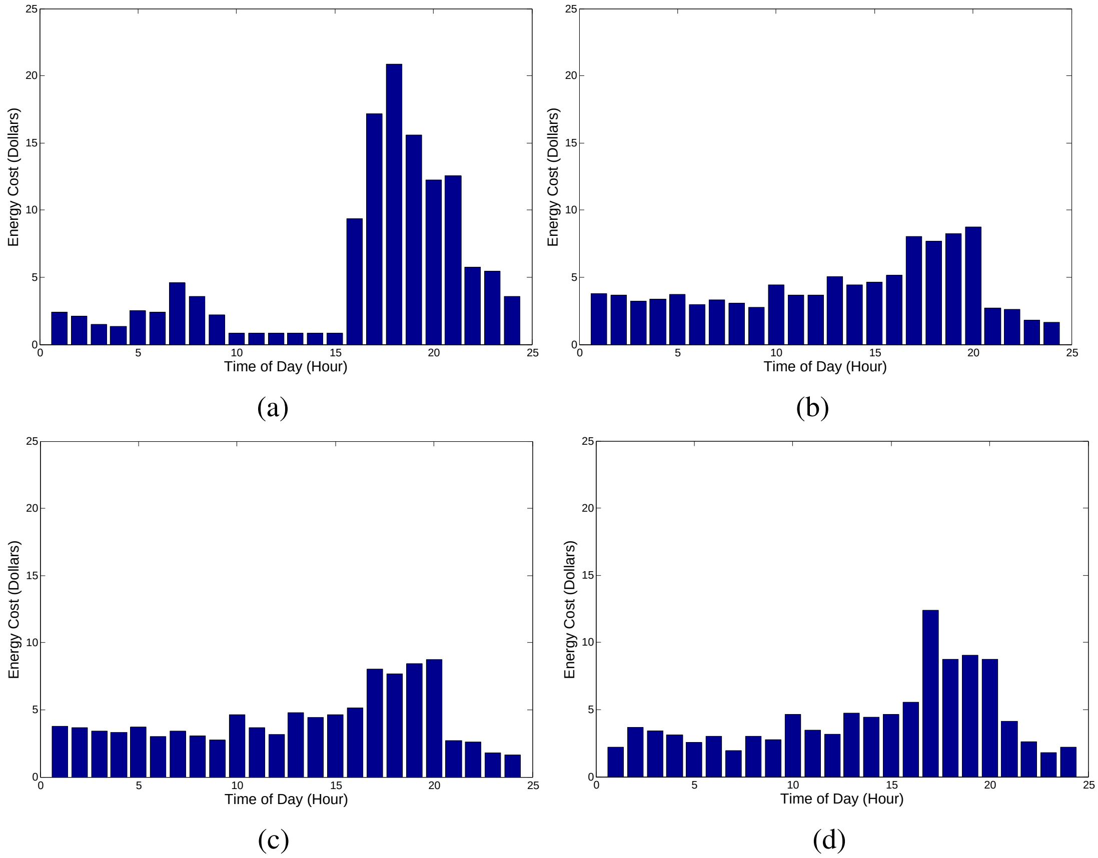


Figure 23: Energy consumption cost when (a) algorithm is not deployed (b) algorithm based on TS is deployed in smart meter (c) algorithm based on BB is deployed in smart meter(d) algorithm based on P-MCTS is deployed in smart meter.

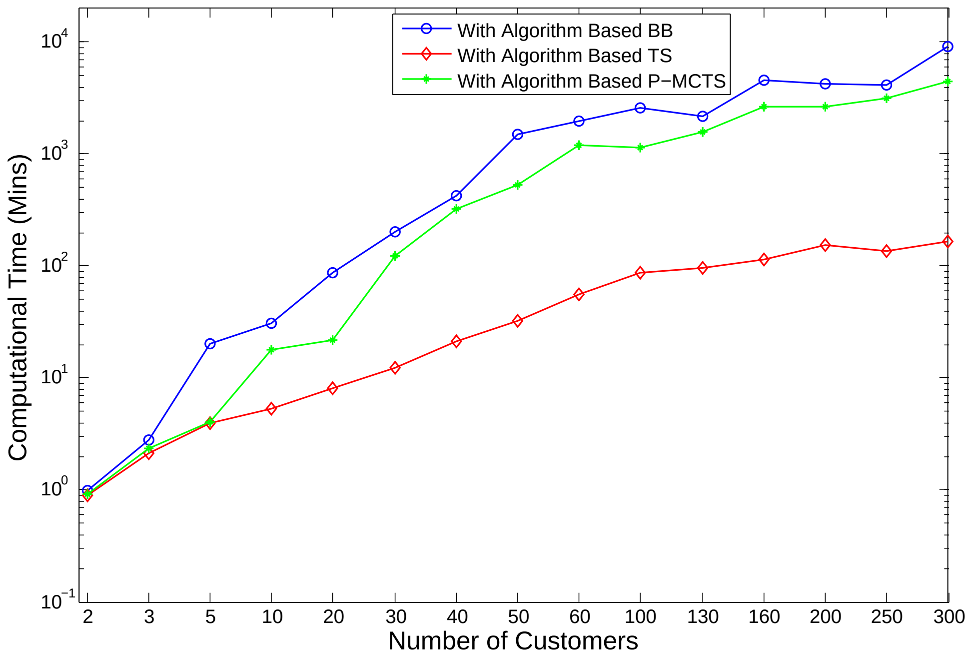


Figure 24: Computational time of the algorithm based on TS, algorithm based on BB and the algorithm based on P-MCTS.

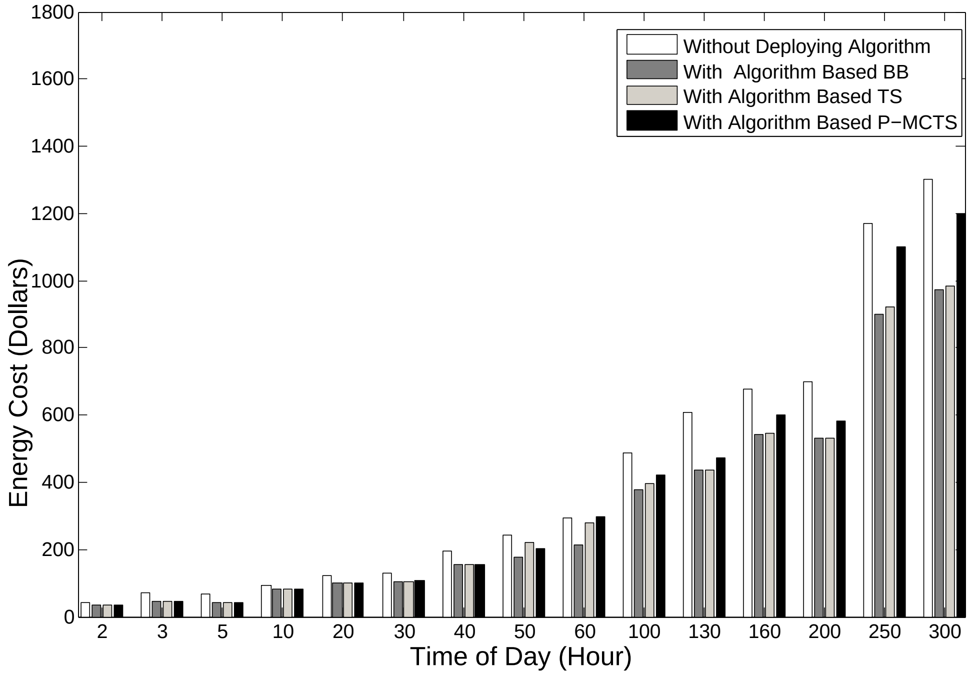


Figure 25: Total system cost comparison for different number of customers and scenarios.

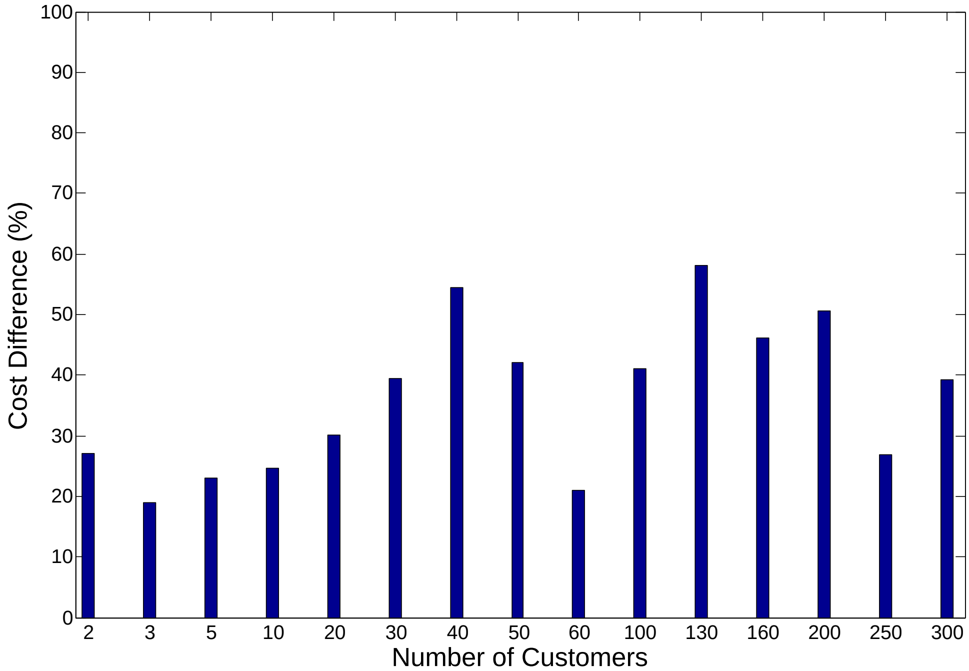


Figure 26: Total system cost comparison between the SSMC and MSMC systems.

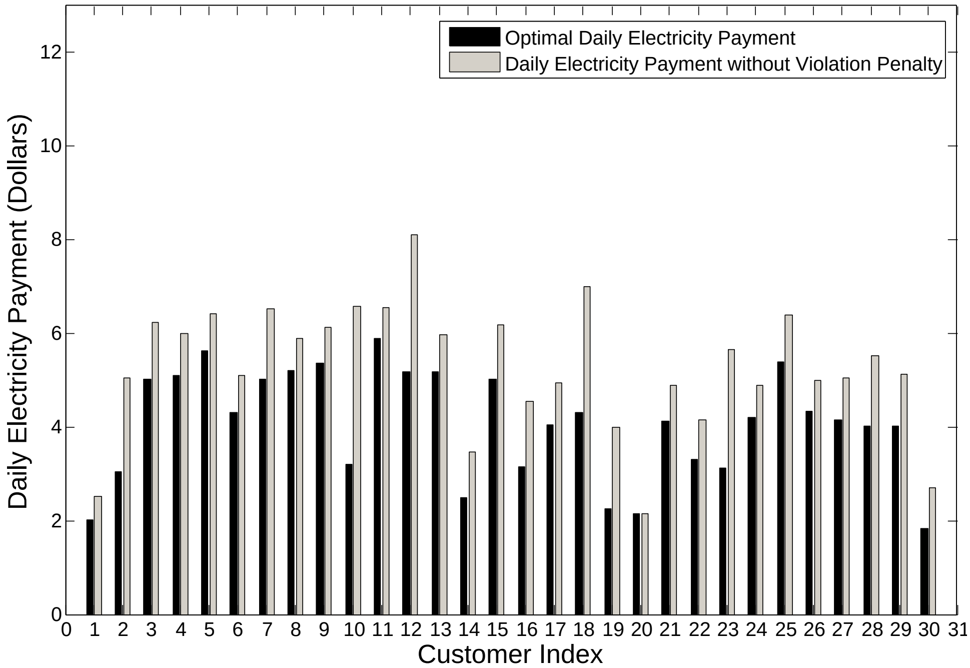


Figure 27: Customers' bills without applying violation penalty.

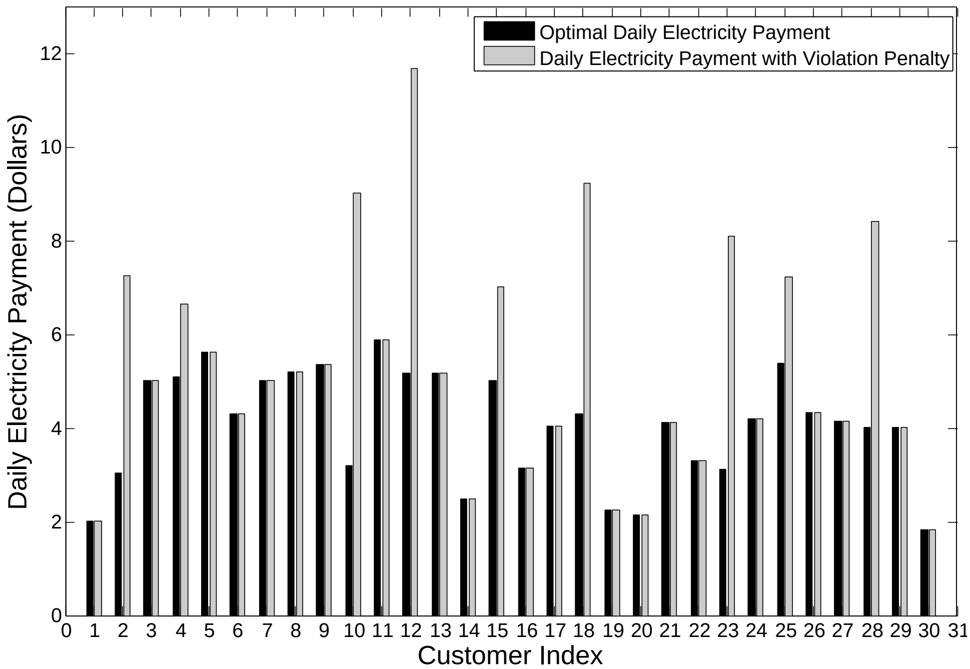


Figure 28: Customers' bills with applying violation penalty.

Chapter 5: Conclusion

Group Autonomous Demand-Side Management (ADSM) programs provide practical mechanisms to coordinate energy consumption for the purpose of achieving smart grid-wide objectives, such as reducing the energy cost, reducing the Peak-to-Average Ratio (PAR), and increasing the penetration of Renewable Energy Sources (RESs). In this work, a group ADSM program, where the customers cooperate to reduce their energy cost payment through scheduling the future energy consumption profiles, is investigated. Two systems are considered; Single-Source Multiple-Customers (SSMC) system and Multiple-Sources Multiple-Customers (MSMC) system. The SSMC system consists only of a central energy source shared among the customers. On the other hand, in addition to a central energy source, the MSMC system consists of distributed Renewable Energy Sources (RESs) and Distributed Storage Elements (DSEs). An aggregative game-theoretic approach is considered for the energy consumption scheduling in the SSMC system, while for practicality aspects a combination of a Deterministic Energy Management (DEM) approach and an aggregative game-theoretic approach is investigated in the MSMC. A novel energy consumption billing mechanism is developed to account for the impact of customers' violations on the performance of both systems and how to deal with such violations to ensure a higher level of fairness. This mechanism increases the systems' fairness level, and hence, it encourages the customers' participation level for achieving the systems objectives. In order to consider the computational complexity and limitations of the group ADSM programs, a sophisticated yet efficient energy consumption scheduling algorithm based on Tabu Search (TS) is proposed. In addition to the ability of achieving the near-optimal energy schedules, the computational time is reduced to a large extent compared to the energy scheduling algorithm based on Parallel Monte Carlo Tree Search (P-MCTS) and the benchmark energy scheduling algorithm based on Branch and Bound (BB).

The simulation results confirm the advantages of the proposed billing mechanism to the fairness level of the systems. It is shown that the performance of the algorithm based on TS is comparable to the benchmark algorithm based on BB results. However, the computational time needed is considerably less. Moreover, it is shown that the proposed algorithm performs better in terms of solution quality and computational time compared to the algorithm based on P-MCTS. The computational time difference between the three algorithms does not vary much for small number of customers, but the differences become apparent in hundred multiples as the number of customers increases. Furthermore, due to the utilization of RESs and DSEs in the MSMC system, the total system cost is reduced by 60% and the level of greenhouse emissions is guaranteed to be lessened, compared to the SSMC system. In addition, the resultant energy consumption profiles of the proposed algorithm are shown to be flattened and evenly distributed.

The results in this paper can be extended in several directions. First, the group ADSM programs presented here, being directly applicable to customers like households, can also be extended to larger contexts, such as commercial and industrial sectors. Second, the programs can be extended to address both shifting and reducing energy consumption. This can be done by utilizing energy cost functions which depend on both the energy consumption at each hour and the total daily energy consumption. Third, more factors and parameters can be incorporated into the power systems, such as specifying a threshold on the amount of energy that can flow over power lines. Fourth, the stochastic nature of the RESs and DSEs can be considered.

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Vita

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