DISSERTATION

AGGREGATOR-BASED RESIDENTIAL DEMAND RESPONSE APPLICATIONS AND CARBON TAX IMPOSITION ON FOSSIL-FUEL GENERATORS

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ABSTRACT

AGGREGATOR-BASED RESIDENTIAL DEMAND RESPONSE APPLICATIONS AND CARBON TAX IMPOSITION ON FOSSIL-FUEL GENERATORS

Smart Grid Initiative started after realizing the urge for changes in conventional electric power grids. These changes should be made in response to a number of emerging issues in the electricity industry. The increasing involvement of renewable energy technologies, either as large-scale generators or as small-rated distributed generators (DGs), poses a challenge for the grid. The renewable energy generators being intermittent and uncontrollable brings worrying uncertainty at the supply side of the grid. This uncertainty makes the grid's operators anxious about balancing generation with load, which is a necessary condition for the security of the power system. Demand side management (DSM) offers a promising solution for the uncontrollability of renewable energy. Residential customers, through new entities called demand response (DR) aggregators, can bring DR services for addressing the aforementioned intermittency in supply.

A cost-minimization framework is set for power supply-demand adjustment with the involvement of variable resources (i.e., renewable energy generators). The resources in the power supply-demand adjustment problem are *demand reduction through aggregators, power flow exchange between areas, and balancing generators' services*. The method is simulated in the IEEJ East 30-machine test system after dividing it into 4 areas. The results of the followed method show a lower cost than the traditional method of using only balancing generators' services. This work builds on a previous work of researchers from Keio Univ in Japan.

DR aggregators also use the Smart Grid Resource Allocation (SGRA) approach, which is a load shifting technique done by a DR aggregator. The DR aggregator performs a heuristic optimization in order to move part of residential appliances from peak to off-peak times. The effects of integrating multiple aggregators into the transmission level power grid are studied and simulated in the Roy Billinton test system (RBTS) after dividing it into 2 areas. The results show peak demand reductions, electricity prices reduction, and lower peak-to-average ratio (PAR) for the system under consideration. In line with integrating DR aggregators, a carbon tax function from the work of Prof. W. Nordhaus, a Nobel Memorial Prize winner in economics sciences, is adopted to design a carbon emission-based tax function and apply it to the fossil fueled generators in the system. The adopted carbon tax leads to less dispatch of coal and natural gas-based generators. As a result, CO_2 emissions reduction is achieved and calculated using the set math models. The DR applications prove to represent a complementary element to the imposition of carbon taxation in achieving emissions-reduction. That is, imposing carbon taxation drives increases in electricity prices, while applying DR reduces the mean electricity price by lowering the PAR of the system load profile.

In addition, a test bed is designed to find a relationship between the aggregator's performance and utility pricing mechanisms. The experiment aims to find how the utility pricing mechanisms affect profitability of the aggregators and peak load shifting. These pricing mechanisms include fixed tariff, time-of-use (TOU) pricing, and real-time pricing (RTP). The simulation-based study shows that aggregators make the highest profits when run in parallel with utilities applying fixed tariffs, while they make the highest shifted peak load when run in parallel with utilities applying RTPs.

Furthermore, survey-based data about the use patterns of three smart home appliances are incorporated in the SGRA approach. These three appliances include dishwasher, washing machine, and dryer. Beside using data about these appliances, additional rescheduling constraints are proposed to improve the comfort of participating customers. The results show profitability for the aggregator by using actual data of home appliances in tandem with additional rescheduling constraints to increase the comfort level of participating customers.

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NOMENCLATURE

Latin Letters

a, b and c	Coefficients of generator's cost function
AMI	Advanced Metering Infrastructure
A_{start}	Start time of an asset's availability window for rescheduling
A_{dur}	Duration of an asset's availability window for rescheduling
B	Expense for buying electricity from the bulk electricity market
b_i	Coefficient of balancing generators cost function at area *i*
$B_{i_a j_b}$	Transmission susceptance between nodes i_a and j_b
CCS	Carbon capture and sequestration
CF	Capacity factor
CIP	Customer incentive pricing
CO_2	Carbon dioxide
$c_{b_i}\left(s_{b_i}(t)\right)$	Cost function of the balancing generators at area *i*
$C(P)$	Total cost function of a fossil-fueled power plant
d	Runtime duration of an asset;
DER	Distributed energy resources
DG	Distributed generation
DR	Demand response
DRA	Demand response aggregator
DRX	Demand response exchange
DSM	Demand side management

E	Emission rate of a generation unit
EE	Energy efficiency
EMS	Energy management system
EV	Electric vehicle
$E_{reduced}$	CO_2 emissions reduced during a 24-hour period
$F_i(t)$	Cost function of supply-demand balancing resources in area i
$f_i(\boldsymbol{\phi}_i(t))$	Cost function of voltage phase angle changes at area *i*
$f_{\rho_i}(t)$	Cost function of receiving negative load from the aggregator at area *i*
GHG	Greenhouse gas
G_h^{taxed}	Energy produced by a generator in hour h after taxation
$G_h^{untaxed}$	Energy produced by a generator in hour h before taxation
HEMS	Home energy management system
HVAC	Heating, ventilation, and air conditioning
IEEE	Institute of Electrical and Electronics Engineers
IEEJ	Institute of Energy Economics, Japan
ISO	Independent System Operator
LMP	Locational marginal price
L_h^b	Load at bus b of the RBTS system at hour h
L_h^{PJM}	Load of PJM at each hour h,
L_{peak}^{PJM}	Peak load of PJM
L_{nom}^b	Nominal load of bus b on the RBTS system,
M	Number of areas in the power network
MCF	Marginal cost function

MEP	Mean electricity price
N	Payment received for selling a negative load
n_i	The number of nodes at area *i*
N_{ij}	The set of nodes that connect area i to area *j*
OPF	Optima power flow
PAR	Peak-to-Average Ratio
P	Power rating of an asset
P_{ij}	Active power flow from area *i* to area *j*
$p(t)$	Spot market price
$p_i(t)$	Retail electricity price at area *i*
PJM	Pennsylvania, Jersey, Maryland Power Pool
PV	Photovoltaic
RES	Renewable energy source
RGGI	Regional Greenhouse Gas Initiative
RTP	Real-time pricing
R_{tax}	Tax revenue collected from a power plant in a 24-hour period
S	Revenue from selling energy to participating customers
$\boldsymbol{s}_b(t)$	Outputs of a balancing generators
s_i^a	Forecast supply at area *i*
s_{r_i}	Actual supply at area *i*
SGRA	Smart grid resource allocation
t	Simulation time step
t_{start}	Original start time of an asset

t_{start}^{dish}	Original start time of a dishwasher
t_{start}^{w}	Original start time of a washing machine
t_{resch}	Rescheduled time of an asset
t_{resch}^{d}	Rescheduled time of a dryer
t_{resch}^{dish}	Rescheduled time of a dishwasher
t_{resch}^{w}	Rescheduled time of a washing machine
TCL	Thermostatically controllable load
TOU	Time-of-use
$T(E)$	Emissions rate-based carbon tax
y	Index of annual growth

Greek Letters

α	Parameter for customers' willingness to participate with aggregator
α_A	Scaling factor for each area A
ΔP_i	Power flow change with respect to area i
ζ_{i_l}	Parameter associated with the cost function of voltage phase angle change
$\theta_{i_a}(t)$	Voltage phase angles of nodes i_a
$\theta_{j_b}(t)$	Voltage phase angles of nodes j_b
$\boldsymbol{\eta}(t)$	Generation errors of renewable generators
$\boldsymbol{\rho}(t)$	Amounts of demand reductions
$\boldsymbol{\phi}(t)$	Changes in Voltage phase angles

CHAPTER 1

INTRODUCTION AND OVERVIEW

1.1 Motivation

The electricity industry in the United Stated has been evolving since a number of incidents occurred in 1970s including what is called "energy crisis." Before that time, electricity industry was technology driven when engineers and operators had to focus only on technical issues for ensuring proper power network operation. However, changes pushed for tighter policies and regulations, which promoted open access and competition [1]. These changes bring a number of challenges to the electric power industry such as accommodating intermittent supply sources into the bulk electricity market [2]. In addition, the electricity demand has increased especially as the integration of electric vehicles which draw considerably high-power ratings during charging. As a result, the cost of energy has increased and has been reflected in the electricity market prices being raised [3]. That troubles the utilities supplying electricity because the electricity demand is variant continuously over time. On hot days in the summer, peak demand can be twice as high as average demand [4]. This high peak load to average ratio causes underutilization to some fast responding generation units which are mostly utilized during peak times to serve this passing peak demand. These peaking units are more expensive and not environmentally friendly due to underutilizing them and their high emissions of greenhouse gases (GHGs) [5], [6], [7].

Climate change is a global issue that requires international cooperation. The electricity industry is among the biggest sectors contributing to climate change. Even though the electricity industry is one of the causes, it will be majorly affected by it when energy demand increases for increasing cooling needs, which could strain electricity generation and transmission infrastructure [8]. In 2018, the emission of CO_2 by the electric power system in the U.S. accounted for about

33% of total U.S. energy-related CO_2 emissions. 65% of the emission was from coal while 33% was from natural gas [9]. As the electricity industry is one of the largest contributors to global warming, it could be the solution by cutting down on the increasing accumulation of CO_2, the principal GHGs, and other GHGs in the atmosphere.

1.2 Objective

Increasing the flexibility of electricity consumption in every sector including commercial, residential, and industrial is a major step toward more efficient power system operation [10], [11]. For proper operation, power system operators have to equate the amount of energy generated with the amount of consumption plus system losses at all times. Otherwise, the system will run into technical problems regarding frequency stability and could collapse eventually. The balancing control has always been at the supply side while the demand side is completely passive. The objective in this dissertation is to involve electricity consumers at demand side in the demand-supply balancing operation and find out how that affects the efficiency of the system in term of operation cost reduction.

DSM has the potential to offer promising solutions for a number of issues in electric power networks [12]. Peak demand is a problem that strains system operators on a daily basis [13]. Every day, there is a period of time when electricity demand rises so rapidly that generators and transmission lines are strained to supply it. Because these generators are used only for this purpose, they are called peaking generators. These peaking generators are fast responding and more expensive than other large-scale generators because they are dispatched temporarily, and their utilization factors are low. The second objective in this dissertation is reducing peak demand through demand response (DR). DR programs are used to make changes to the demand behavior over time. It is used to incentivize consumers monetarily to shift their load from peak time when prices are high to off-peak time when prices are lower, which offers good savings for them. So, the role of the DR aggregators is acting as a mediator between residential customers and the independent system operator (ISO) to bring peak demand reductions into the electricity market.

The effects of reducing peak demands on electricity prices during peak times in the bulk electricity market is also evaluated in this dissertation. The peak-to-average ratio (PAR) is an indicator for the average utilization levels of generators [14]. Higher PARs mean lower average utilization levels for generators and less revenues for these generators. Hence, PARs are also calculated before and after shifting the loads to show the effects of the peak demand reductions brought by the DR aggregators.

In addition, this dissertation shows a proposal of carbon taxation function for fossil-fueled generators because it is proved that carbon taxation is a good strategy to mitigate the emissions rates of GHGs [16]. The objective of imposing tax on CO_2 emissions is to inhibit the amount of CO_2 emissions in electricity industry. Our goal is to find the emissions reduction, tax revenues, and reflection on electricity prices.

The DR aggregators and the carbon tax have a complementary relationship in such a way that both of them achieve CO_2 reduction in two periods of the day. The DR aggregators reduce peak demand which leads to CO_2 reduction at peak times. On the other hand, the carbon tax discourages the utilization of base-load fossil fueled generators which are more competitive at off-peak times. Hence, the dissertation provides a comprehensive approach for cutting down on CO_2 emissions at peak and off-peak times.

1.3 Scope

This dissertation specifically studies, evaluates, and design a framework for the integration of DR aggregators into electricity market. It integrates multiple aggregators in wide-area power grids to improve the performance of the system with regard to minimizing balancing services cost and lowering the PAR and electricity prices.

First, it builds on the work of the researchers at Keio University with regard to negawatt (i.e., negative load), trading mechanism [17]. It adds DR aggregators into minimizing the cost of the power supply-demand adjustment operation. The DR aggregators are integrated into a multiple-area power network for the power supply-demand adjustment operation. The aggregators are involved to bring negative load to the system operator. This trading mechanism is simulated in the IEEJ East 30 machine test system after dividing it into 4 connected areas.

Second, it studies the impacts of integration DR aggregators into electricity markets on the reducing peak demand, the energy cost to provide peak demand, and also electricity prices in the bulk electricity market. The aggregator's work mechanism was proposed in the smart grid resource allocation (SGRA) paper [18]. The addition in this dissertation to applying multiple aggregators into the transmission power system to evaluate the impacts on the system and the bulk electricity market. The aggregators are to participate in the market through DR exchange (DRX) market for selling peak demand reductions to the system operator. The Roy Billinton test system is used to simulate the integration of DR aggregators on the transmission level of the power network.

Furthermore, an emission rate-based carbon tax function is proposed for fossil-fueled generation units in line with the integrated DR aggregators. The dissertation demonstrates the effect of carbon taxation on electricity prices, emissions reduction, and tax revenues.

1.4 Software Means

MATLAB® code is used for solving the minimization problem model in chapter 3 and for plotting the graphs in chapter 3, 4, and 5. The original code was written by the researchers at Keio university. A permission was gained to modify the code for the purposes of the studies in this dissertation. In addition, PowerWorld® software is also used to simulate The Roy Billinton test system and perform different analyses related to power engineering including optimal power flow, generators dispatch graphs, marginal costs, and time step simulation. Excel sheets are used for calculations and graphs shown throughout the dissertation.

1.5 Dissertation Chapters Description

The remaining chapters of the dissertation are organized as follows: a literature review about wide-area DR programs is presented in chapter 2; an application of negawatt trading mechanism between DR aggregators and the ISO is presented in chapter 3; Chapter 4 explains the integration of multiple aggregators into electricity market and the application of carbon tax function on fossil fuel-based generators; the relationship between utilities pricing systems and the behaviors of the aggregators is presented in chapter 5; chapter 6 presents the incorporation of rescheduling constraints into the SGRA approach using survey-based data about home appliances; and chapter 7 concludes the dissertation and mentions potential future work.

CHAPTER 2

WIDE-AREA DR PROGRAMS IN SMART GRID: A LITERATURE REVIEW

2.1 Overview

Utilities have been practicing the principles of DR since early 1980s because it is significantly useful for correcting a number of technical and economic issues related to power systems. These issues include the increasing integration of renewables and the deferral of investments in new infrastructure due to increases in electricity demand. However, the Smart Grid Initiative has quickened the pace of DR development and deployment. The smart technologies such as communicating meters made it possible for the concept of low-scale load aggregation to be integrated into electricity markets. Nevertheless, there are still several problems to be addressed with regard to the participation mechanism of DR resources into wholesale electricity markets. Therefore, this chapter presents a literature review about DR programs and their applications as well as the concept of load aggregation and the aggregator's role in the markets. Then it mentions the technical advantages of implementing DR programs on other issues and concepts such as the integration of intermittent resources, the application of ancillary services, and the notion of virtual power plants. Furthermore, the technical and administrative challenges of DR programs are thoroughly presented. The SGRA problem is presented as a framework for aggregation of residential load and providing it to the electricity markets as DR resources [18]. The negawatt trading is also presented as an example of using DR resources for the supply-demand adjustment problem [17].

2.2 Introduction

Due to the increasing growth of electrical energy demand in industrial, commercial, and residential levels, the traditional power system faces several obstacles in keeping up with this rapid increase in electricity demand. In the United States, the power system infrastructure has been suffering from aging machines and equipment that are vulnerable to failures [19]. This increasingly reduces the system overall reliability as the power system facilities have been aging with time of operation. Expanding the capacity of power system in generation and transmission sectors might not be the wisest decision since it is expensive and inefficient.

The Smart Grid Initiative that took place in the last decade has aimed to transformation of the vertically structured power system. One of the purposes of Smart Grid is increasing the efficiency of the system by introducing the participation of consumers in the system. However, the participation of customers should be controlled by DSM which aims to reduce the instantaneous demand by changing the energy demand patterns of end consumers particularly at peak demand hours [20]. DSM incudes different types of techniques such as energy efficiency (EE), energy conservation, and DR. The energy efficiency technique increases the system efficiency by using more efficient devices such as installing compact fluorescent bulbs instead of incandescent bulbs. Additionally, it introduces energy efficient technologies such as automatic thermostats. As for the energy conservation technique, it involves using less resources by changing consumption behaviors. These behaviors include reducing thermostat for heating systems or using clothes and dish washing machines at their full capacities. Lastly, DR introduces responsive load to the system by involving electricity markets and pricing systems.

DR programs have been integrated into the power system and electricity market practice [21]. The power system has witnessed a quick growth of DR programs that are being called on more repeatedly and widely. The integration of Smart Grid technologies such as Advanced Metering Infrastructure (AMI) and others will certainly increase the implementation of DR programs for residential sectors in daily basis operations because it provides RT access to usage data [22].

The integration of DR programs into the distribution network has been lately an active research subject. There has been a number of suggested frameworks for DR practices involving information and communication technologies, control structures, load management methods, and pricing systems. there have also been other active research subjects related to DSM such as energy efficiency and energy conservation, yet they are out of scope of this chapter. Therefore, this chapter shows a high-quality literature review about wide area DR programs and its applications in the Smart Grid. The rest of the chapter is structured as follows: Section 2.3 is defining the concepts of DR programs and load aggregation. The DR impacts on electricity markets are discussed in Section 2.4. In section 2.5, DR for intermittent resources is presented. DR for ancillary services is discussed in section 2.6. The SGRA framework is presented in section 2.7. Section 2.8 presents the negawatt trading work proposed by researchers at Keio university [17]. Challenges are discussed in section 2.9. Lastly, Section 2.10 presents the main conclusions.

2.3 DR

A number of emerging technologies in Smart Grid has made it possible for end-consumers to participate in energy dispatch. That is, customers identify their real time power load by using AMI. This opens the door for lots of DSM designs and structures to be integrated into the system as DR programs. The U.S. Department of Energy defines DR as “changes in electric usage by end-use customers from their normal consumption patterns in response to changes in the price of electricity over time, or to incentive payments designed to induce lower electricity use at times of high wholesale market prices or when system reliability is jeopardized" [23]. DR is purposed to change the traditional patterns of electricity consumption which causes a number of technical problems to the system including dramatic variations of power demand during the day. Hence, DR practices play a role in the power system dispatch in a way that improve the total efficiency of the system including peak shaving, efficient renewable energy utilization, lower electricity cost, and faster response.

2.3.1 DR Programs

Loads are commonly categorized into two types: critical loads and flexible loads [24]. Critical loads are fixed at all time and constant in a way that cannot be shifted or curtailed. As for flexible loads, they are elastic to prices and their consumption behaviors can be modified according to pricing schemes. Flexible loads can be divided into three classes. First, basic loads which consume power for a certain period of time but can be shifted to other times. Second, interruptible loads that can be isolated any time, even during its operation, which is more flexible than the basic loads. Third, consistently switching loads whose operation status is identified by set points such as air conditioning systems.

DR programs are mainly divided into two categories which are price-based DR and incentive-based DR [24]. In priced-based DR programs, the consumers are given different energy prices that are time-varying. The major price-based DR programs are involved with TOU rate and critical peak rate in which customers are charged with changing prices at different times during the day such as peak-time and off-peak time. A similar time varying pricing approach that is also considered under this category is RT or dynamic pricing. For DR programs applying these pricing mechanisms, electricity prices vary continuously at different time periods throughout the day. As for incentive-based DR programs, customers are encouraged by financial incentives to reduce their demand at system stress or for contingencies. Direct load control and interruptible loads are main incentive-based program. In direct load control, loads are controlled distantly by the electricity utility and provide fast curtailment services. In interruptible load programs, users are given a lower rate when they reduce their loads at system stress situations.

2.3.2 Load Aggregation

As the number of participants, who are willing to adjust their flexible loads in DR programs, increases, the availability of the controllable loads rises when needed for solving the supply-demand mismatch. In addition, a minimum rated load is required to participate in the current electricity markets. Hence, aggregation of small loads is a regulating method to integrate low-rated loads into the wholesale electricity markets.

The aggregation of a large number of loads can be controlled and organized by an entity called demand response aggregator (DRA). The main job of DRA is scheduling DR resources in the wholesale electricity market and sell it at the spot market price as demand reductions [24]. Large customers were already considered for load aggregations which are commonly from industrial and commercial sectors. Nevertheless, residential low-rated loads and electric vehicles (EVs) are recently being considered for aggregation and participation in the market thorough regional aggregators. By providing a bid in the wholesale market, the aggregator is given the assigned DR schedule once the market is cleared. There are different ways for reducing loads including load curtailment, utilization of distributed generation, load shifting, and energy storage facilities. Through communication capabilities, aggregators can be connected to each other at multiple levels for control and technical reasons. For instance, EVs and thermostatically controllable loads (TCLs) can be overseen by different aggregators, but these aggregators can also be integrated into an upper-level aggregator as a hierarchical structured control framework.

2.4 DR Impacts on Electricity Markets

The effect of DR in electricity market is studied in [25]. It has implemented a day-ahead market-clearing method to show the effects on the system. The used method aims to maximize the social welfare by reducing the electricity cost. Customers can submit their flexible load bids when they are elastic with the consumption timing. This bidding technique gives the system operator a method to reduce the demand-supply unbalancing risks after closing the gate in the market. The clearing-market prices drop as the shifting bids increases, which benefits all customers even those who are not load shifting bidders. This mechanism has shown several advantages over conventional bidding mechanism in a way that enhances the economic efficiency of the electricity market by reducing the costs of supplying the demand, manages the unmet demand, and offers a substantial saving to the demand side as the amount of load shifting is increased.

In [26],a study was conducted to measure the consumption sensitivity of air conditioning to hourly change of electricity costs. Based on the consumption behaviors in the presence of time dependent pricing, the system operator outlines a purchase-bidding approach. The results show that by using this price-demand sensitivity strategy, not only can the electricity prices be reduced during peak hours but the volatility between hours can be diminished as well.

Utilizing bidirectional communication between a customer and a supplier is a key element in optimization purposes for use in DR programs. Customers can use bidirectional communication to optimize their energy use in order to maximize their utility in a form of electricity cost reduction [27]. It is also a major element for implementing the SGRA-based aggregator framework. The interaction between customers and suppliers can happen on an hourly basis through an algorithm to monitor the energy consumption during the entire day. These algorithmic interfaces can be integrated into customer premise energy management systems (EMS).

DR could be practiced based on multiple techniques such as RT rate, TOU rate, critical peak rate, demand-side bidding, curtailable load and direct load control. Therefore, planning a suitable pricing DR system is a major concern for reliable and efficient smart grid. In [23], a practical pricing system is suggested based on customers' classification who are supplied with different pricing approaches to select so they are actively participants in the pricing process. The customers are divided into different categories based on their information such as upper limit of load adjustment, elasticity coefficient, and marginal cost. Then, cost minimization is achieved thorough an appropriate pricing scheme as a non-linear programing optimization.

2.5 DR for Intermittent Resources

Renewable-based energy generation is intermittent, variable, and non-dispatchable by its nature. That makes it difficult for this kind of generation to compete in the market with other dispatchable generation such as coal and natural gas-based generation [24]. DR can play a key role in accommodating this volatility in generation because it provides a flexible and cost-effective integration process. To illustrate this issue with wind-based generation, it is notable that there are cases at which the energy produced out of wind turbines exceeds the nominal demand, which can cause energy waste sometimes. However, shifting load-based DR can be utilized to reschedule a number of customers' loads from peak times to such times when there is excessive generation. That make it cost-effective and, subsequently, enables more penetration of renewable energy-based production into the power system since there will be shifted demand to be met at their peak production. References [28] and [29] study the advantages of DR on wind generation in the short-term trade. As for photovoltaic (PV) uses, a study proves that heating, ventilation, and air conditioning (HVAC) fan can be utilized for power control to mitigate the variability of energy produced through PV panels during cloudy daytime which is proved to be more cost-effective than other used approaches [30]. Chapter 3 presents an application of negawatt trading involving DR aggregators in order to maintain supply-demand balance with the increasing involvement of intermittent resources.

2.6 DR for Ancillary Services

Electric power systems need ancillary services for balance and reliability purposes. These services include spinning and non-spinning reserves to balance power deficiencies. They can also regulate the frequency by quick power injections and commitment to keep the system frequency within the acceptable limits [27]. Ancillary services can be provided by flexible loads with fast response through DR. therefore, independent system operators are required to allow DR to participate in the ancillary services markets in accordance to Order 719 issued by FERC [31]. In addition, it is expected that EV owners make the largest profit by participating in the ancillary services market [31]. As presented in [33] and [34], techniques are explored to utilizing TCLs to control power and frequency imbalances. In [33], state estimation approaches used to trace the performance of heterogeneous TCL groups, in opposition, a stochastic and robust programming and a model predictive controller are used to define the setpoints of TCL in [34].

2.7 Smart Grid Resource Allocation Problem

The SGRA mechanism is basically a load shifting technique applying the principles of DSM [18]. In this problem, the aggregator is a for-profit entity between the system operator and the customers. It uses a genetic algorithm-based optimization framework to find rescheduled times for some participating smart appliances in the residential sector. The objective of the optimization framework is to maximize the aggregator's profit by deciding the optimal schedule for all or some of the schedulable assets that agree to partake in the aggregator business. The assets reschedule is determined one day in advanced for the next 24-hour duration. To encourage consumers to participate, the aggregator offers a dynamic pricing called customer incentive pricing (CIP) which is designed to be lower than the forecast utility pricing (e.g., RT pricing or TOU pricing).

The aggregator must receive information about the schedulable appliances in order to perform the optimization and set the schedule. Precisely, the aggregator receives the following information about each reschedulable asset:

- power rating (in KW)
- runtime duration (in 15-min intervals)
- availability window for rescheduling (start time A_{start} and duration A_{dur})
- original scheduled start time

By collecting the schedulable assets characteristics, the aggregator implements heuristic optimization framework in the form of a genetic algorithm to determines a schedule of smart appliances and the CIP. The aggregator's mechanism for making a profit in the electricity spot market is clarified in the following points:

- To promote customer's participation, the aggregator offers CIP which must be lower than the forecast utility pricing to justify the rescheduling discomfort for consumers.
- The aggregator aims to reschedule appliances away from peak times. Consequently, the aggregator offers demand reduction and sells it to the system operator during peak times when the market spot market is at its highest.
- The aggregator reschedules appliances to other periods of lower spot market prices. The aggregator must buy energy to supply its participating customers' appliances.
- The customers pay the aggregator at the prices of the CIP which is generally lower than the utility prices. This realizes saving for customers and revenue for the aggregator as well.

The daily aggregator's profit is calculated using (1)

$$P = N + S - B \qquad (1)$$

where S is the revenue from selling energy to participating customers at the CIP; N is the payment received for selling a negative load (i.e., demand reduction) to the ISO at spot market pricing; and B is the expense for buying electricity from the bulk electricity market at spot market pricing for supplying the rescheduled customer assets. These three terms, $N, S,$ and B, are calculated as follows for each participating asset among a set of reschedulable loads. The 24-hour period is divided into 96 intervals of 15 minutes.

$$S = \sum_{t=t_{resch}}^{t_{resch}+d-1} \frac{cip(t) * P}{4} \qquad (2)$$

$$N = \sum_{t=t_{start}}^{t_{start}+d-1} \frac{p(t) * P}{4} \qquad (3)$$

$$B = \sum_{t=t_{resch}}^{t_{resch}+d-1} \frac{p(t) * P}{4} \qquad (4)$$

where t_{start}, t_{resch}, and d are the original start time of an asset, the rescheduled time of an asset, and the runtime duration of an asset; P is the power rating of an asset; cip(t) and p(t) are the CIP and spot market price. t is the simulation time step (in 15 minutes).

The proposed optimization framework is validated to be profitable for the aggregator. The paper simulates the optimization of a large-scale system combining 5,555 residential customers and 56,642 schedulable appliances over a 24-h period using real pricing data. Even though the optimization objective is maximizing the aggregator's profit. it also realizes another benefit for the power system performance. It specifically reduces the PAR of the load profile by shifting appliances from peak hours to other times.

2.8 Negawatt Trading

A negawatt trading mechanism is proposed in [17]. Negawatt means the amount of negative load (i.e., demand reduction) the consumers provide to the market as DR resources. In this particular study, the purpose of the negawatt trade is to minimize the supply-demand balancing cost by utilizing balancing generators and power flow changes along with demand reductions. However, it does not involve an aggregation entity between the ISO and the consumers to facilitate and coordinate the optimal demand reduction required for the supply-demand balancing operations. In chapter 3, an application of DR aggregators integrated with negawatt trading in a multi-area power grid is presented.

2.9 Challenges

One of the main requirements for the implementation of DR aggregation is a communication infrastructure for bidirectional transfer of data among different entities of the electric power system. That is the system needs information transfer capabilities between the independent system operator and the DRA as well as the DRAs information centers and the customers or the EV charging stations. From an economical prospective, the needed communicational infrastructure represents the major cost to implementing DRAs [21]. Internet networks are proposed for use in ordering and transferring information among DRAs and home energy management system (HEMS) or appliances. Yet, the utilization of internet facilities itself cannot be done without dealing with some challenges because power grids do not generally use such medium and the availability may raise a number of concerns.

It is suggested that the deployment of AMIs is a right solution for multiple benefits including DR aggregations. However, acute attention should be paid to the investment cost in AMIs and other associated facilities needed for DRAs control and management. Therefore, when it comes to implementing large scale DRA, scalability problems should be considered [35]. This can be addresses by centralized and decentralized methods with different complexities in computation and optimization approaches as well as performance times [36]. A promising method is suggested in [37]to deploy AMIs for broadcasting a single common signal to all loads, which takes respectively short time scales. However, choosing appropriately signals for broadcasting is still a significant issue.

Another challenge associated with implementing DR programs is latencies. Involved with AMIs, which can influence the performance and balance of the network. The effects of these latencies can be shown when fast response moments or regular control actions are needed. For example, latencies have a large impact when supplying spinning reserve by DR means. In addition, AMIs and smart meters SMs are usually owned by entities such as retailers or distribution system operators. Therefore, having another entity like the DRA to use them represents security and privacy problems [21].

It is notable for the demand to go up before and after the DR utilization. These two events of increasing consumption are referred to as "lead and rebound" effects [38]. The lead effect comes before a DR implementation as customers expect the DR happening. For example, a customer switches on the air conditioner of a building before noon for precooling the building in order to cut down the air conditioning after noon load when the DR takes place then. The rebound effect can be observed after the DR occurrence finishes when the consumption level exceeds the baseline. Furthermore, asymmetrical DR distribution on phases during the DR times may cause phase unbalance situations. It is also a challenge for regulation service by DR aggregation to be able of not only providing but also absorbing power.

Implementing large scale DR programs whether price- based or incentive-based programs goes through a number of obstacles regarding customers' comfortability. Because these programs affect the user's comfort level, worthy incentive must be involved in such programs to encourage users' participations. Additionally, price-based programs raise a reliability issue resulted from load shifting from peak to off-peak times when the electricity prices are lower. The complexity of dynamic pricing programs may cause customers' hesitation to participate and interact with them [38].

On the demand side and the grid, there are different types of controllers and equipment that raise a serious issue for DR aggregation. For interoperability purposes, there must be standards and communication protocols unified among different devices and control frameworks.

In sum, a properly designed framework for DR aggregation is required. This framework must set appropriate standards and protocols for information exchange among different DRAs in a hierarchical model. Reference [39] shows modelling proposals for DR aggregation.

2.10 Conclusion

DR programs are promising methods to benefit the electric power system on multiple levels. Due to proper management of demand side electricity consumption, DR is a tool to solve several technical problems including the peak demand curve. Therefore, it reduces the total cost of electricity production, which is beneficial for utilities and customers.

Toward the goal of using DR aggregation for the favor of the electric power system, an application of DR aggregators integration into electricity markets through negawatt trading is presented in chapter 3.

CHAPTER 3

NEGAWATT TRADING MECHANISIM

3.1 Overview

In this chapter, we propose a distributed power supply- demand management mechanism in a RT market by utilizing various resources including demand reduction, balancing generators, and power flow changes. The proposed method aims to minimize the cost of balancing the supply with the demand. We simulate the results on the IEEJ EAST 30-machine system with four connected areas. The results show the feasibility of the proposed method and the establishment of a relationship between the DR aggregator and the ISO.

This chapter is a verbatim reproduction of the work accepted and published to a peer -reviewed conference proceedings in [40]. As requested by the copyright holder, the published article is listed in references section. The numbering of the figures and tables has been modified to satisfy the formatting requirements of the dissertation.

3.2 Introduction

The Smart Grid Initiative is modernizing the US electric power system by integrating new technologies that generally improve supply reliability, transmission security, distribution reliability, and energy efficiency. Along with other attributes of a smart distribution system, active consumer participation through responsive demand plays a major role and enables the Smart Grid Initiative to realize some desired objectives [41].

However, the participation of a residential customer in existing bulk electricity markets is not feasible due to a minimum amount of energy required for trading [42]. So, an entity that aggregates the DR resources of customers is essential for enabling the participation of residential and other low power-rated end-users. Such an entity, termed “an aggregator”, collects load information about the participating customers within its purview via a dedicated communication infrastructure and enables the customers to participate in the bulk electricity markets by representing them.

The study in [43] proposes a negawatt trading, which is a relationship between the ISO and consumers in order to encourage consumers to reduce their consumption for supply-demand balancing in a real time market. Through the trading mechanism proposed in [43], consumers receive an incentive price for reducing their load at a certain time. The incentive price is merely dependent on the amount of load reduction. So, when receiving the incentive price from the ISO, consumers adjust their demand to maximize their social welfare, which is the difference between their utility of consumption and the cost of consumption. The ISO keeps updating the incentive price at each hour until reaching an optimal demand that minimizes the cost of power supply-demand adjustment operation. The method aims to minimize the balancing cost by utilizing balancing generators and power flow changes along with demand reductions; however, it does not introduce an aggregation entity between the ISO and the consumers to facilitate and coordinate the responsive demand for providing negative loads.

In RT markets, the participation of DR aggregators can increase the flexibility of the power system. Increasing the flexibility of supply and demand from both producers and customers' ends may facilitate the integration of large-scale renewable-based generators into the grid. DR programs realize the flexibility at the demand side and these programs allow the customer, who would not be allowed otherwise, to participate in electricity markets.

Although it has its own technical and regulation challenges, the DR aggregators have been established in some deregulated electricity markets around the globe. One of the expected advantages of the DR aggregators is solving the power supply- demand management challenges caused by the uncontrolled variations at the generation ends. These variations stem from the increased presence of renewable energy-based generators [44], [45]. The renewable energy-based generation is expected to increase in the future as the entire world has a target of 800 GW renewable generation by 2035 [46]. Using balancing generators alone, as in the conventional power management method, may not be effective. Hence, the demand aggregation concept is looked to as an accommodating means to the integration of renewables.

This chapter presents a distributed DR aggregator-based power management mechanism in company with power flow changes and balancing generation, thus representing an enhancement to the work presented in [43]. The work in this chapter shows a new mechanism aims to minimize the cost of the power supply-demand management done by the ISO, which is responsible for maintaining proper and secure operation for the power network. The contribution of this work is designing an optimization framework to reduce the power adjustment cost by utilizing DR aggregators, tie-line flow changes, and balancing generators. The rest of the chapter is organized as follows: section 3.3 explains the integration the SGRA mechanism with negawatt trading, section 3.4 describes the power network model, section 3.5 describes the problem formulation, section 3.6 presents the verification of the proposed method, and section 3.7 presents some conclusions and future work.

3.3 Integration of the SGRA Mechanism with Negawatt Trading

An aggregator-based demand resource allocation problem was previously introduced and solved using heuristic optimization [18]. An evolutionary algorithm was employed to reallocate the resources/appliances in residential load points for a 24-h period in the day-ahead market for achieving peak reduction. In addition, the algorithm produces CIP for encouraging customers to participate with the aggregator. Information about forecast spot market pricing, forecast utility pricing and some characteristics about the reschedulable loads is entered as inputs into the evolutionary algorithm. The required characteristics of a schedulable load include its power rating, runtime duration, rescheduling availability start time and duration, and original scheduled start time.

The objective of this heuristic optimization method is maximizing the aggregator profit. The overall mechanism by which the aggregator makes its profit is explained as follows:

- The aggregator incentivizes customers to allow for rescheduling their appliances; the customers receive CIP and rescheduling times.
- The aggregator sells the total load, of those customers who allow their load to be rescheduled, to the ISO as negative load.
- The aggregator aims to maximize its profit by rescheduling appliances from peak times when prices are high. Hence, it is profitable to sell negative load to the ISO.
- The aggregator buys electricity to supply the rescheduled appliances typically at off-peak times when prices are lower.
- The aggregator sells the purchased electricity to its participating appliances at CIP, which is generally lower than the utility pricing to be incentivizing.

The aggregator-based resource allocation mechanism proposed in [18] validates that optimizing for economical purposes leads to profits to different parties in the electricity market including the aggregator itself and its participating customers as they pay less than they would pay if they chose to be supplied through the utility at its RT pricing. This chapter combines the mechanism of selling negative load in the SGRA problem (from [18]) and the power management technique via negawatt trading (from [17]).

3.4 Power Network Model

The model of the power network considered in this chapter consists of a number of areas, M, connected by a number of branches. However, the power flowing among the power network areas is subject to physical limitations and there is cost associated with changing the power flow as described later in this chapter. For the purposes of this chapter, we consider four types of participants in the electricity market: power suppliers, power consumers, DR aggregators, and an ISO. The latter is a nonprofit entity that operates and regulates the electricity market and energy transmission. Renewable generators and large-scale generators are both considered in the power network model as suppliers. Figure 3-1 shows the power grid network considered in this chapter.

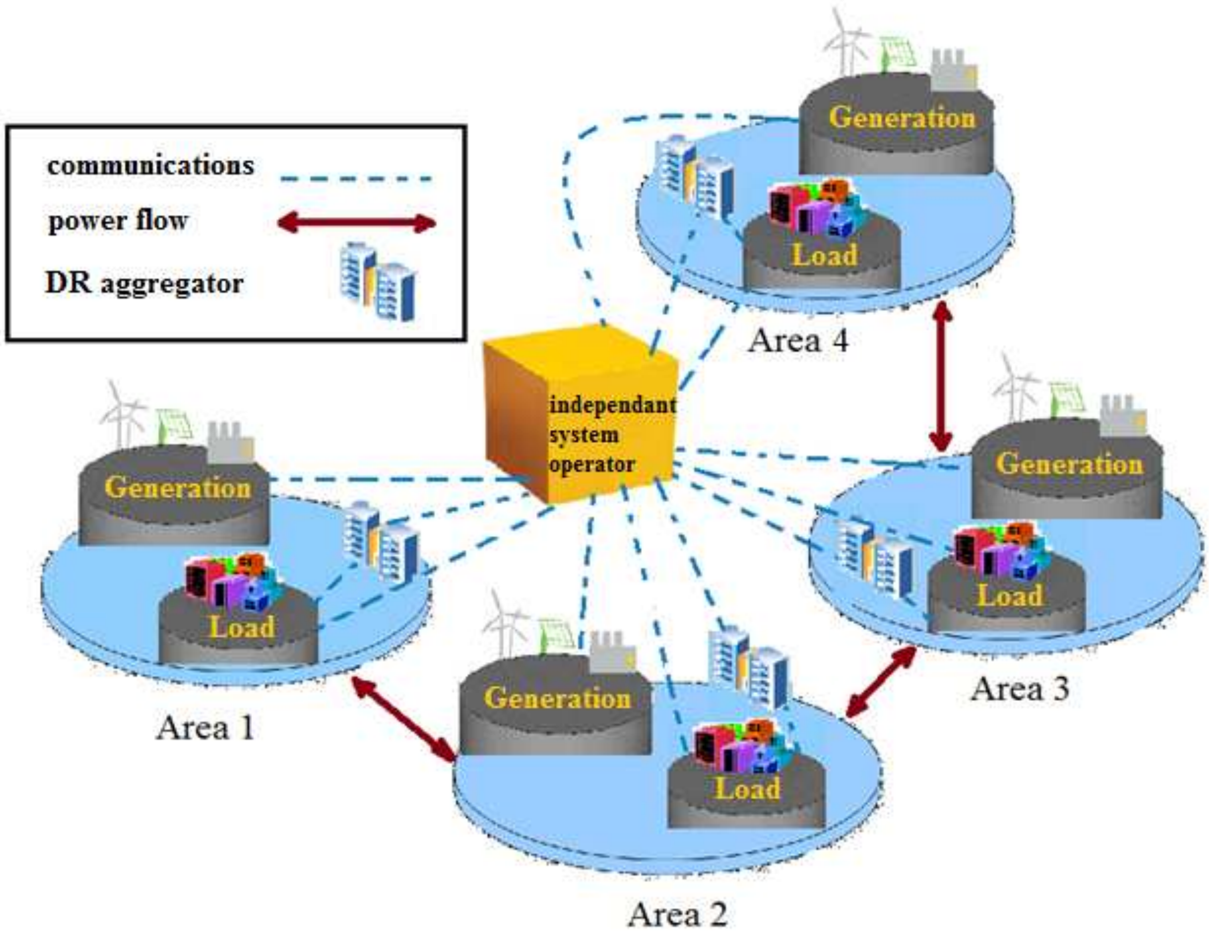

Figure 3-1: The power network model

A DR aggregator is a for-profit entity, which exists between the ISO and the customers, and has the required communicational infrastructure to deal directly with the ISO. Primarily, it provides negative load (i.e., negawatt) and sells it to the ISO for a certain profit. The aggregator decides the best method to obtain the negative load from the customers. It typically incentivizes the customers to allow rescheduling their appliances to other times by providing lower prices. This chapter focuses on establishing a relationship between the ISO and the aggregator, while the aggregator-customer relationship is out of its current scope and is detailed in [18].

On the other hand, the ISO is responsible for operating the power grid and the electricity market. It manages the amount of power supply from balancing generators and the power flow among the areas. It also communicates with aggregators in the network and determines the amount of load reduction for each one of them in negawatt trading.

In the power network model proposed in this chapter, area i has n_i nodes, some of which connect area i to other areas through interarea transmission lines (branches). We assume that the power network has the following simplified properties:

1. The loss from the resistance in the model is ignored.
2. The voltage magnitude at each node is approximately 1 p.u.
3. The voltage phase angle differences between nodes are adequately small.

Under these assumptions, the active power flow from area i to area j at time t can be formulated as follows:

$$P_{ij} = \sum_{(i_a,j_b)\in N_{ij}} B_{i_a j_b} \left(\theta_{i_a}(t) - \theta_{j_b}(t) \right) \qquad (1)$$

where $\theta_{i_a}(t)$ is the voltage phase angles of nodes $i_a, a = \{1,2, \dots n_i\}$, and $\theta_{j_b}(t)$ is the voltage phase angles of nodes $j_b, b = \{1,2, \dots n_j\}$, $B_{i_a j_b}$ is the transmission susceptance between nodes i_a and j_b. N_{ij} is the set of nodes that connect area i to area j.

3.5 Problem Formulation

In [17], a dynamic pricing method is proposed to determine the electricity prices as well as the power supply and demand in each area in the day-ahead market. The objective of the proposed method is to maximize the overall social welfare for the entire power network. In this chapter, we use the day-ahead market data from [17]. The data includes the hourly regional electricity prices which represents the retail electricity prices in each area. For each area, it also includes the demands and the amounts of generation from both renewable-based generators and large-scale generators for a 24-hour period.

3.5.1 Objective

In this work, we propose a RT power adjustment mechanism by utilizing different adjustable resources including balancing generators, power flow changes among areas, and demand reductions. The demand is reduced through the participating aggregators in the network areas, that receive information about the optimal demand reduction at that period in a RT market. The mismatch between the power supply and demand set in the day-ahead market stems from errors in the expected production of renewable-based generators [43]. Mostly, these errors are caused by imperfect weather forecasts. Other sources of shortage in generation that cause differences between actual and forecast generation include sudden failures and unexpected problems for some generators.

To adjust the power supply-demand imbalance caused by generation shortages, the ISO aims to minimize the adjustment cost in the RT market by solving the minimization problem shown in the next section. The outputs of solving the minimization problem determine the optimal amounts of production from balancing generators, the changes in power flow values among areas, and demand reductions set for the aggregator in each area.

3.5.2 Cost Minimization Problem

In the RT market, we propose that the ISO considers the minimization problem to determine the optimal values for the available resources involved in the power adjustment problem. The problem is formulated as:

$$\min_{\boldsymbol{\rho}, \boldsymbol{s}_b, \boldsymbol{\phi}} \sum_{i \in M} F_i(t), \tag{2}$$

$$\text{s. t.} \quad \boldsymbol{\rho}(t) + \boldsymbol{s}_b(t) + \overline{\boldsymbol{B}}\, \boldsymbol{\phi}(t) = \boldsymbol{\eta}(t) \tag{3}$$

where $F_i(t)$ is the cost function related to utilizing resources in area i including the cost of generation, $\boldsymbol{s}_b(t)$ from balancing generators in area i, the cost of changing the voltage phase angles, $\boldsymbol{\phi}(t)$ to change the power flow associated to area i, and the cost of buying negative load or demand reduction, $\boldsymbol{\rho}(t)$ from the aggregator in area i. The variables typed in bold in the above equation to indicate vectors of values related to the areas in the network. That is $\boldsymbol{s}_b(t) = [\boldsymbol{s}_{b_1}(t) \ \cdots \ \boldsymbol{s}_{b_M}(t)]^T$, $\boldsymbol{\rho}(t) = [\boldsymbol{\rho}_1(t) \cdots \ \boldsymbol{\rho}_M(t)]^T$, and $\boldsymbol{\phi}(t) = [\boldsymbol{\phi}_1(t) \ \cdots \ \boldsymbol{\phi}_M(t)]^T$. In addition, $\boldsymbol{\eta}(t) = [\boldsymbol{\eta}_1(t) \ \cdots \ \boldsymbol{\eta}_M(t)]^T$ is the generation errors of renewable generators, which represents the difference between the forecasted generation and the actual generation. M and $\overline{\boldsymbol{B}}$ are the number of areas in the network and the susceptance of the transmission lines connecting the network areas, respectively.

3.6 Verification

This section shows the simulation conditions and the results after applying the proposed power supply-demand adjustment in real-time for 24-hour period.

3.6.1 Simulation Setup

We choose the test system and data used in [17] for simulation. The IEEJ EAST-30 machine model is used to simulate and verify the proposed method [47]. The model is divided to four areas which are connected through a number of branches. Figure 3-2 shows the model used in this simulation.

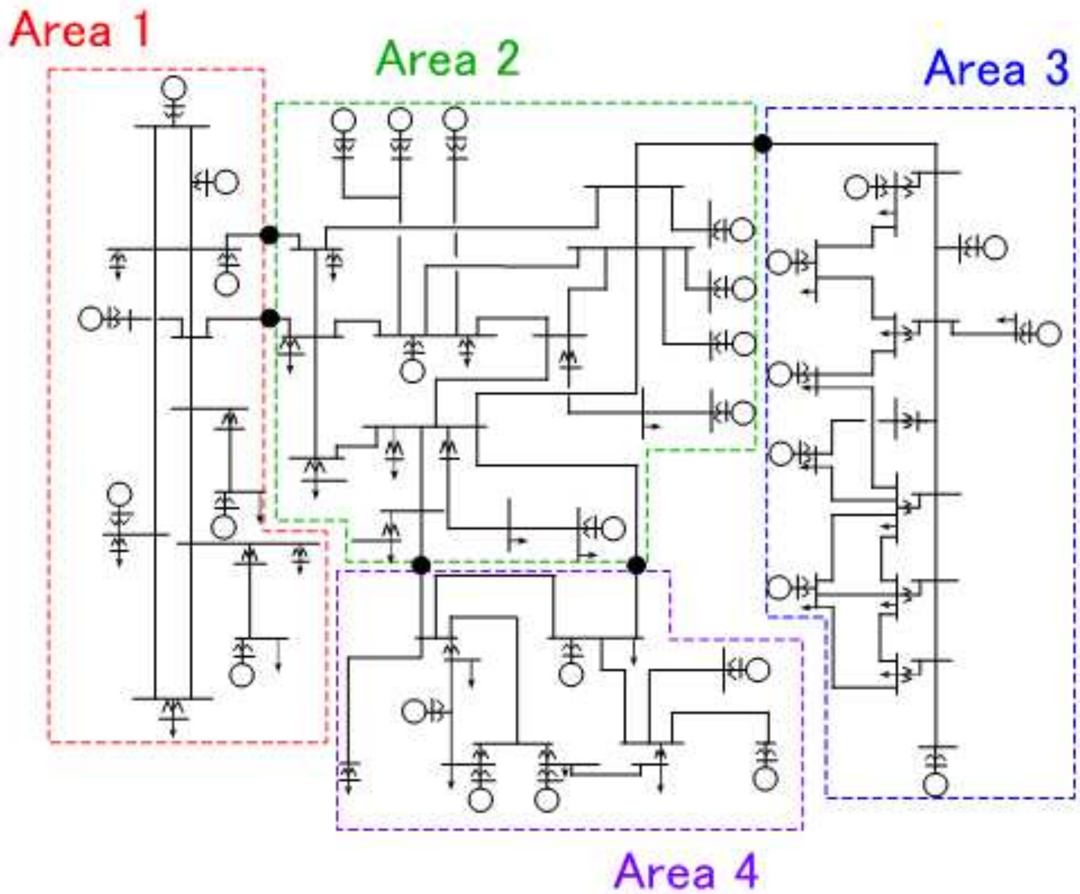

Figure 3-2: IEEJ EAST-30 machine model [6]

Additionally, the day-ahead market trading is supposed to be already conducted and all the data is known to the ISO including the power demand, supply, power flow, and the retail electricity prices at each area for a 24-hour period. The day-ahead market information is obtained from the market trading model in [17]. Figure 3-3 shows the retail electricity prices (in \$/MWh for the IEEJ EAST-30 machine model) determined in the day-ahead market for a 24-hour period in areas 1–4. From the ISO perspective, the cost function of the balancing generators at area i, the cost function of the voltage phase angle change with respect to area i, and the cost function of receiving negative load from the aggregator at area i are the following

$$c_{b_i}\left(s_{b_i}(t)\right) = b_i\, s_{b_i}^2(t) \quad (4)$$

$$f_i\big(\boldsymbol{\phi}_i(t)\big) = \sum_{l=1}^{n_i} \zeta_{i_l}\, \phi_{i_l}^2(t) \quad (5)$$

$$f_{\rho_i}(t) = \rho_i(t)\, p_i(t) \quad (6)$$

where n_i is the number of nodes connecting area i to other areas in the network, and $p_i(t)$ is the retail electricity price at area i ($l = 1,2, \cdots, n_i$). The coefficient of the cost function b_i of the balancing generators for this particular model is derived from the fixed electricity price and the equation shown in [17]. As for the parameter associated with the cost function of the voltage phase angle change ζ_{i_l}, it is set to 1.0×10^{12}.

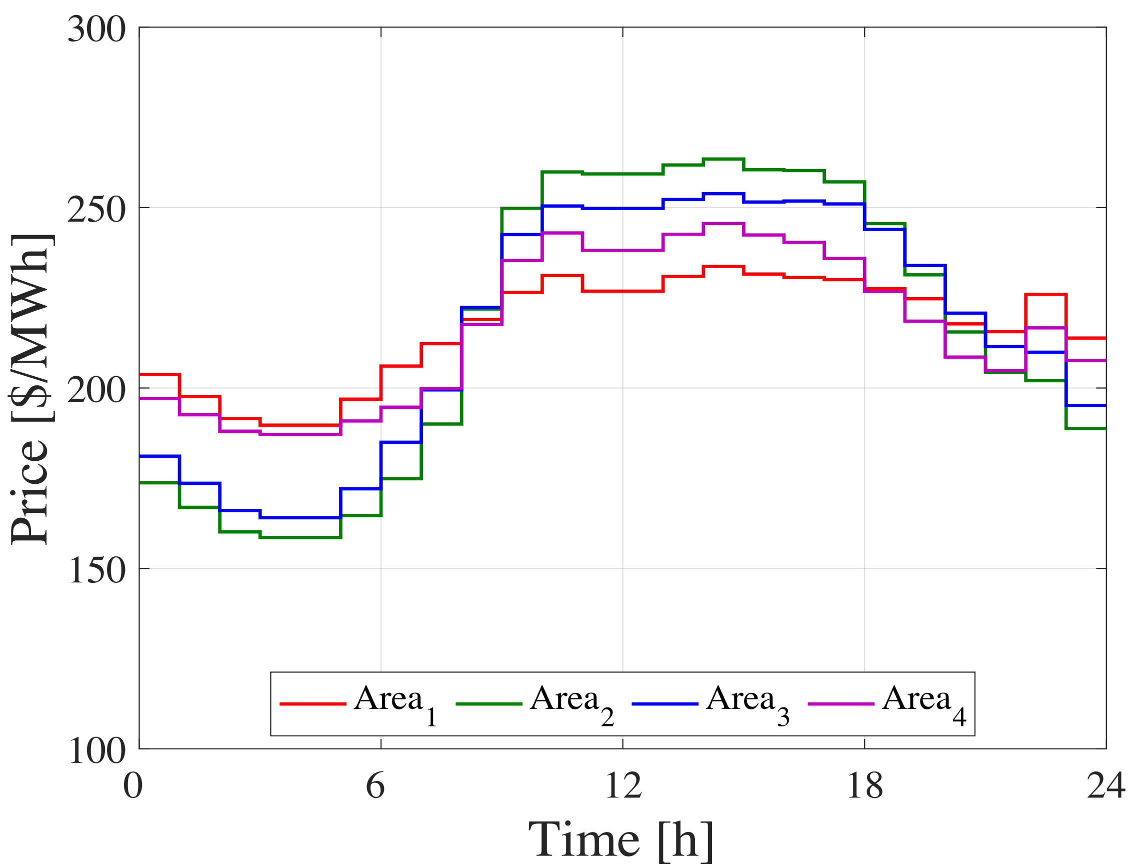

Figure 3-3: Retail electricity prices (in $/kWh) for areas 1–4 of the IEEJ EAST-30 machine model for a 24-hour period [6].

3.6.2 Results

The power flow changes with respect to areas 1–4 are shown in Figure 3-4, Figure 3-5, Figure 3-6, and Figure 3-7 respectively. The negative values in these figures mean that the respective area exports power to other areas through the connecting branches while the positive values means that the area imports power from other areas. In Figure 3-8, Figure 3-9, Figure 3-10, and Figure 3-11, the power production of the balancing generators in areas 1–4 are presented. Using the simulation setup explained previously and applying the proposed algorithm, we verify the feasibility of utilizing the balancing generators, the power flow changes, and the negative load trading between the ISO and the DR aggregators in the power supply-demand adjustment operation. Figure 3-12, Figure 3-13, Figure 3-14, and Figure 3-15 show the results of the power supply-demand adjustment in a real-time market for a 24-hour period at areas 1–4 respectively. The different power adjustment resource quantities at areas 1–4 are utilized to fill the mismatch between actual and forecast supplies with minimums adjustment cost. In these bar graphs, the quantities of the forecasted supply and the real supply are presented, and the difference between them are filled by the available resources. We explain the graph related to area 1 to explain the different quantities in these graphs, and that is applied to the graphs of other areas 2-4. Speaking about area 1, the difference between the forecasted supply of the renewable energy-based generators, s_1^a and the real supply of the renewable energy-based generators, s_{r_1} are covered by the balancing generator, s_{b_1}, the power flow changes among areas, ΔP_1, and the demand reductions, ρ_1.

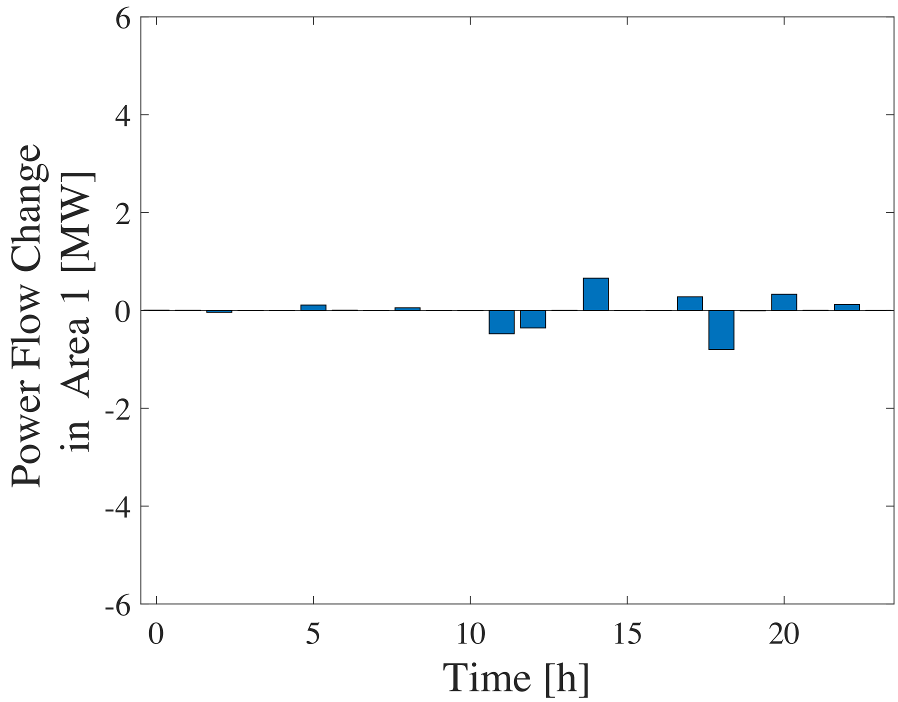

Figure 3-4: Power flow condition at area 1

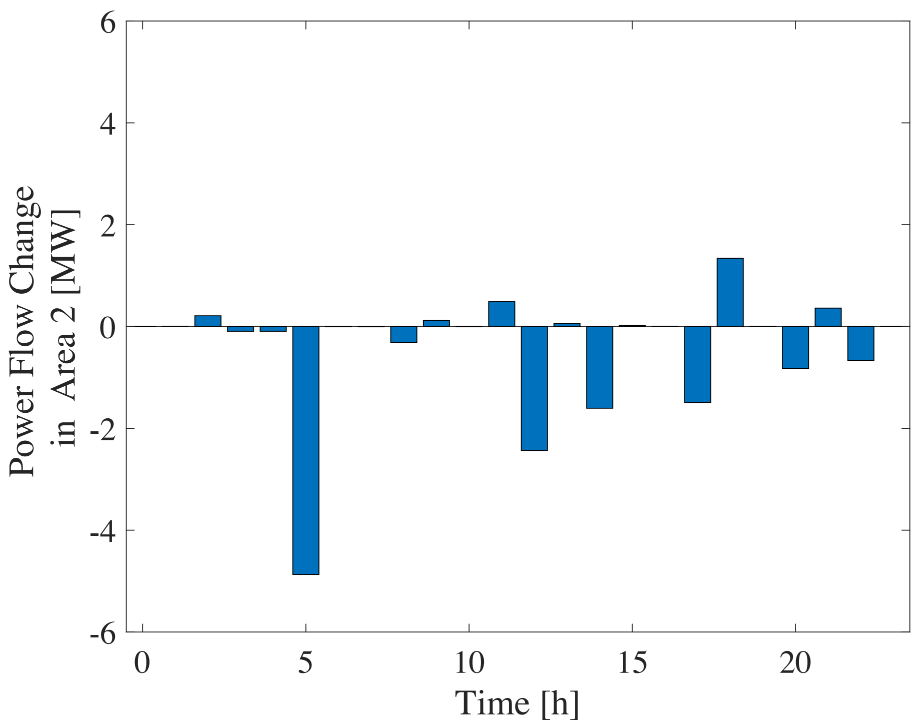

Figure 3-5: Power flow condition at area 2

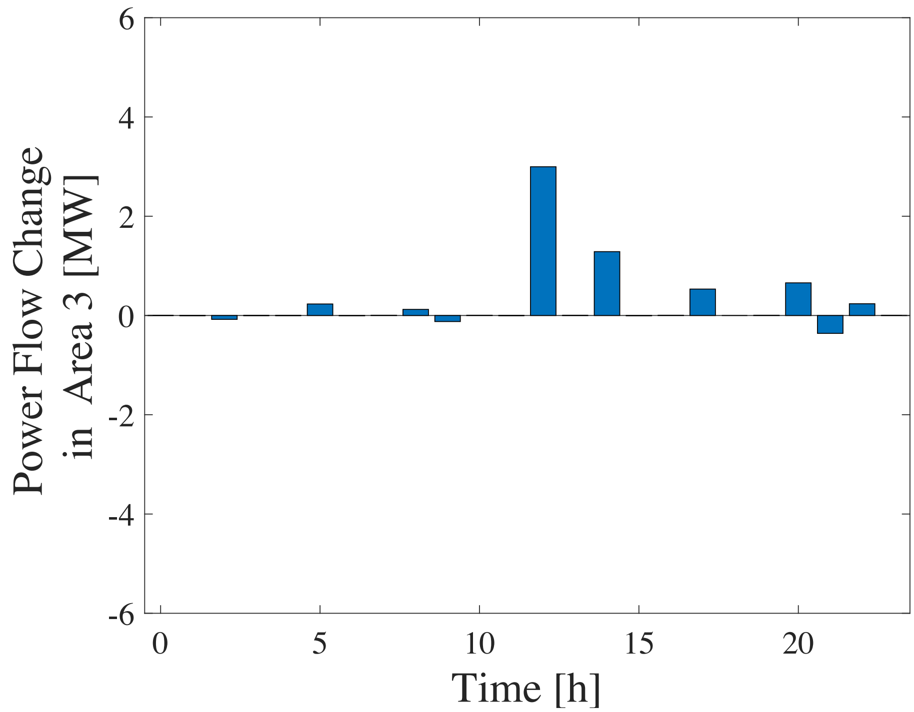

Figure 3-6: Power flow condition at area 3

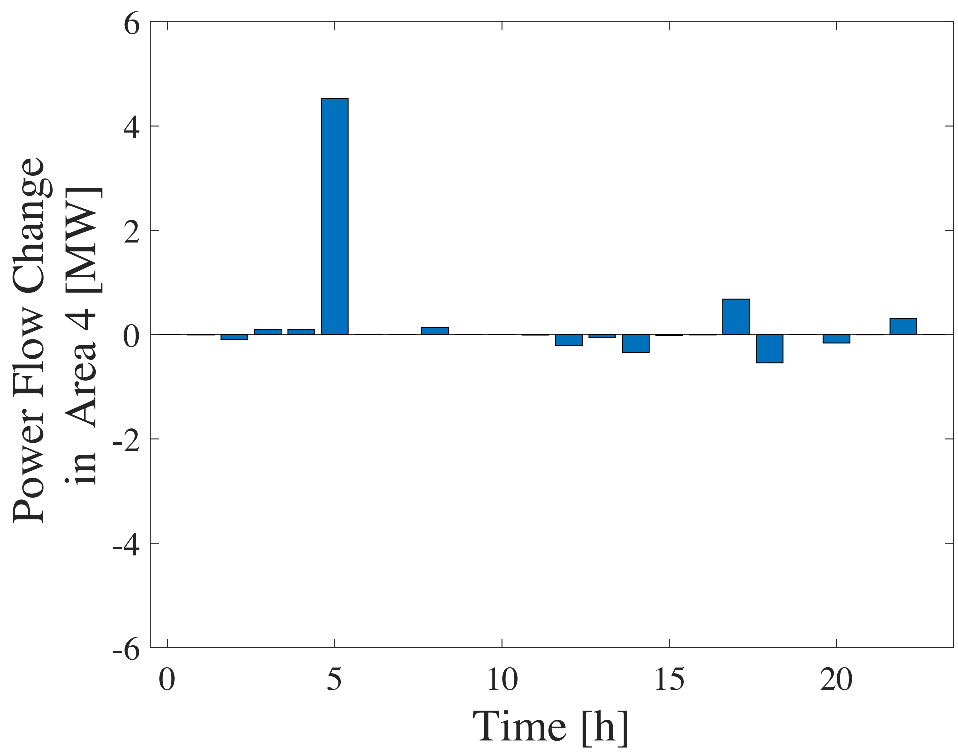

Figure 3-7: Power flow condition at area 4

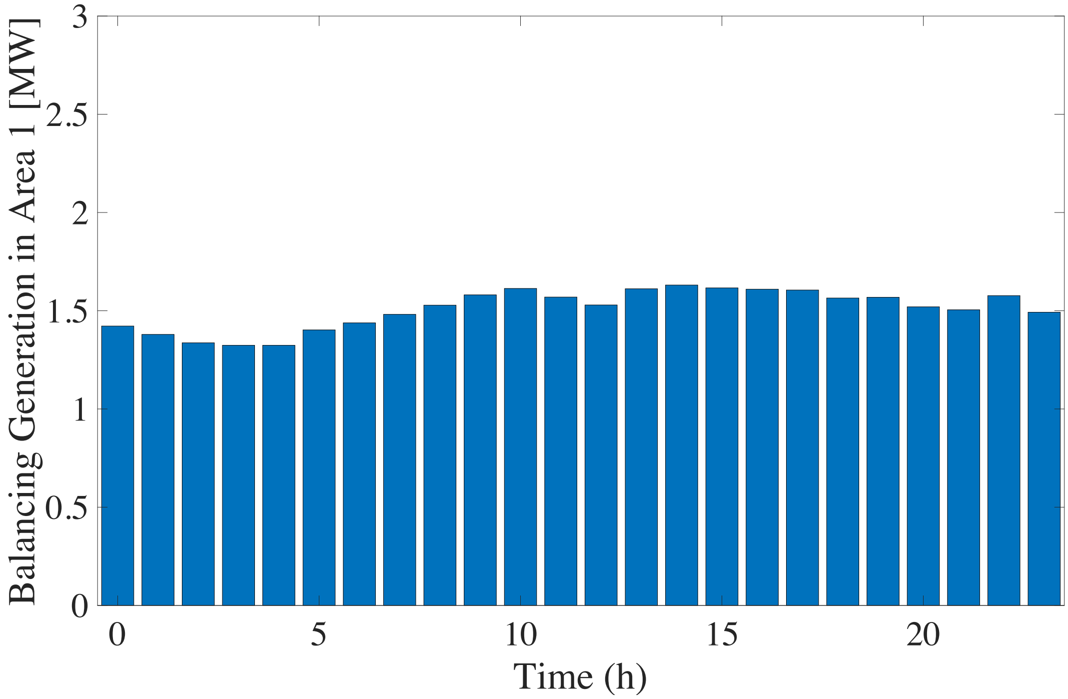

Figure 3-8: Balancing generator production at area 1

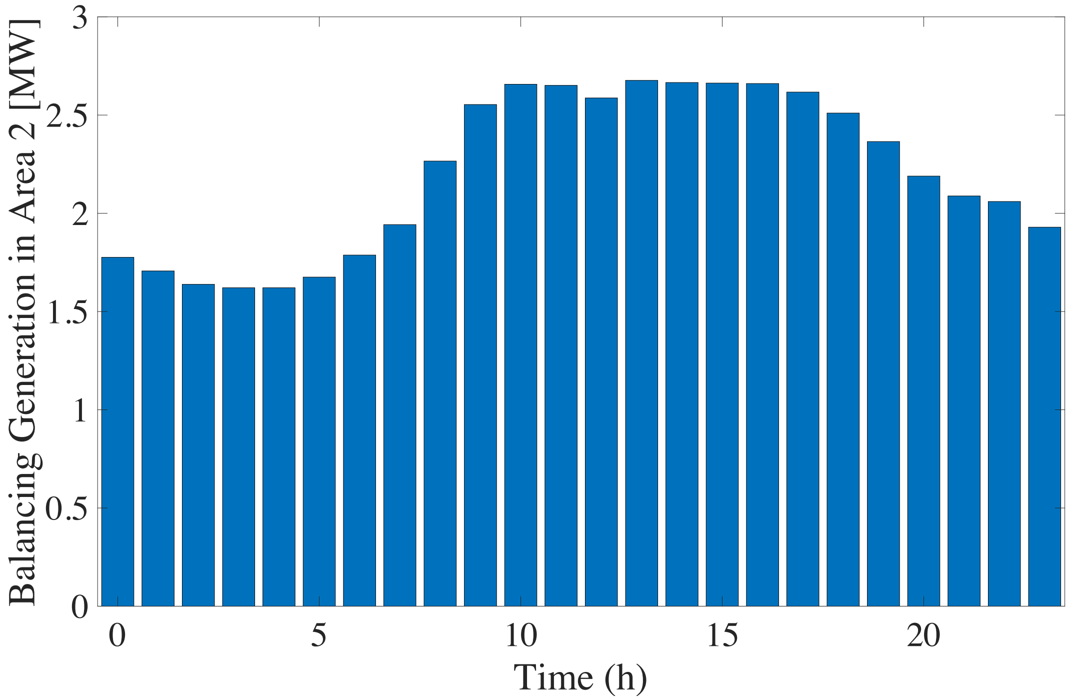

Figure 3-9: Balancing generator production at area 2

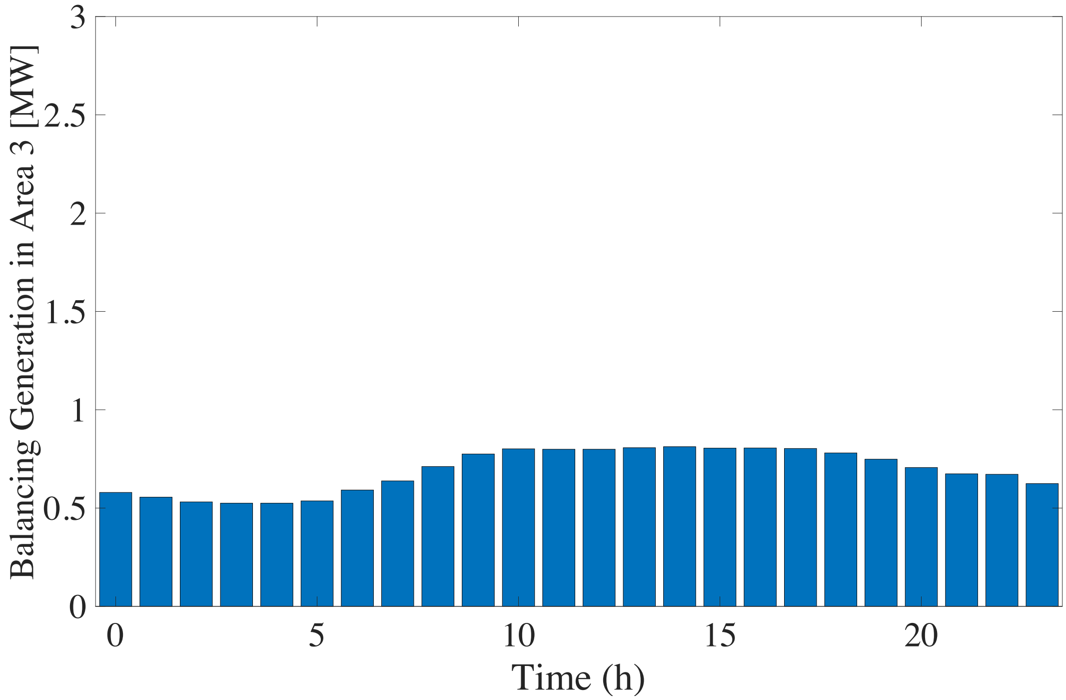

Figure 3-10: Balancing generator production at area 3

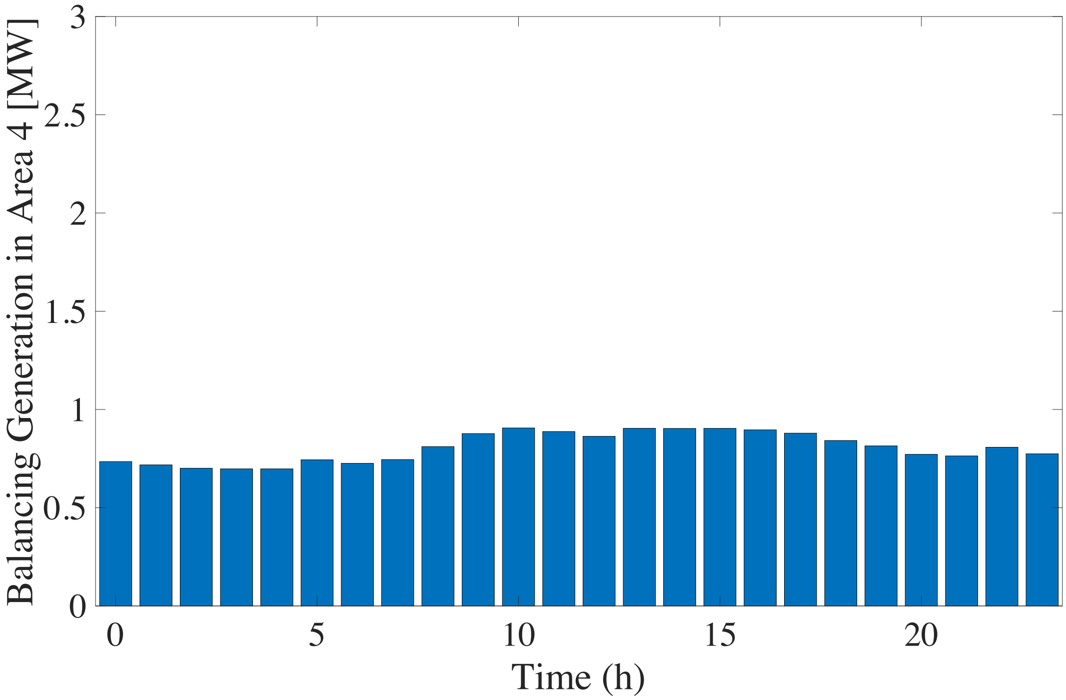

Figure 3-11: Balancing generator production at area 4

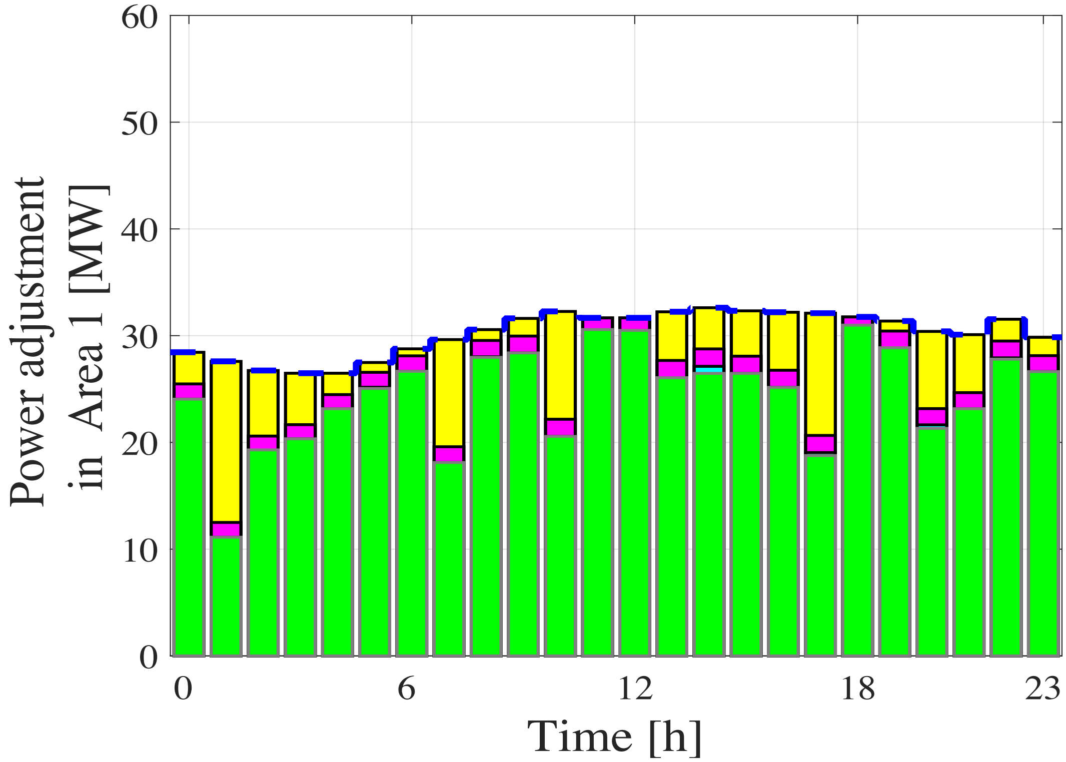

Figure 3-12: Power adjustment in area 1

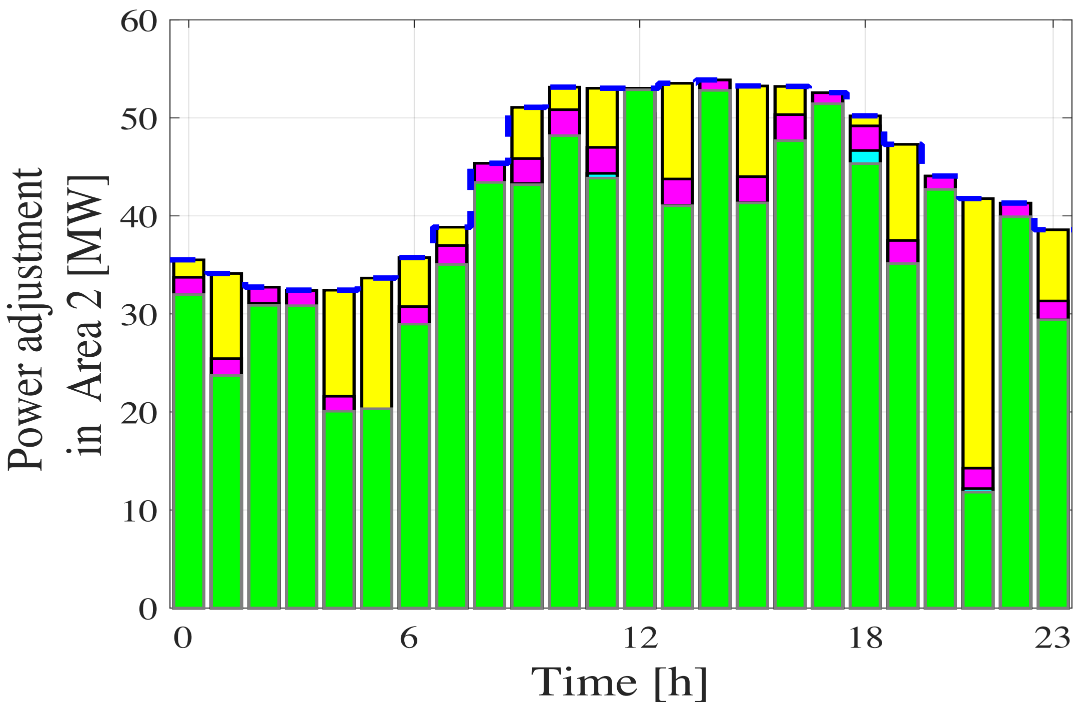

Figure 3-13: Power adjustment in area 2

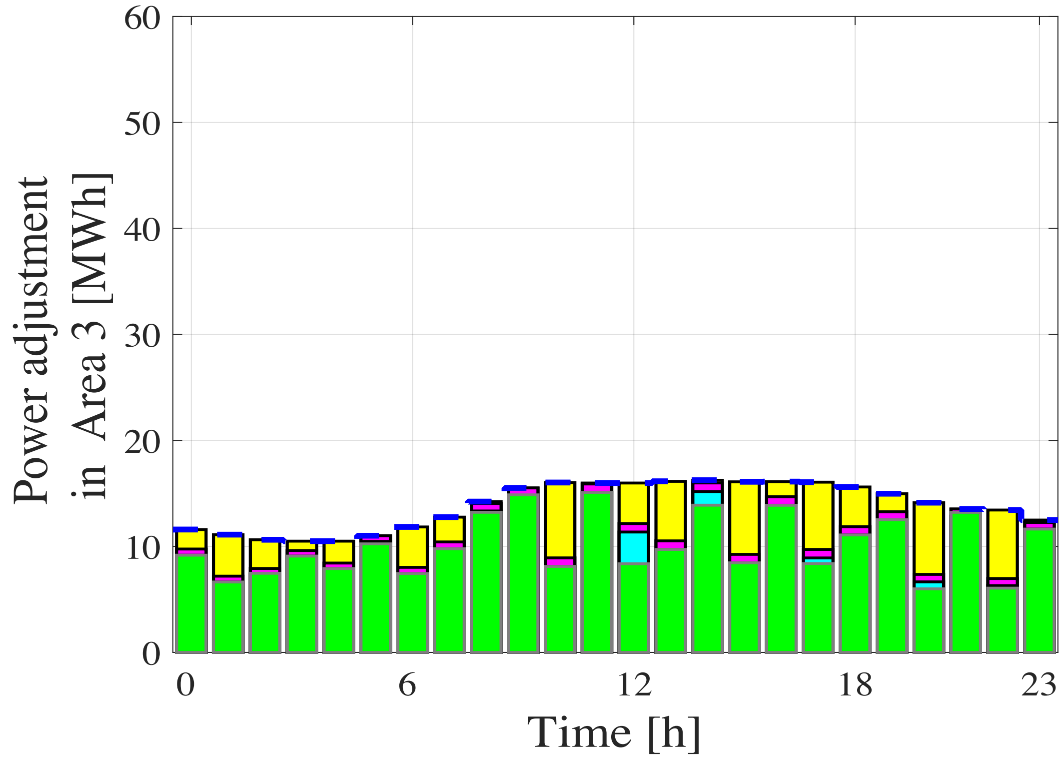

Figure 3-14: Power adjustment in area 3

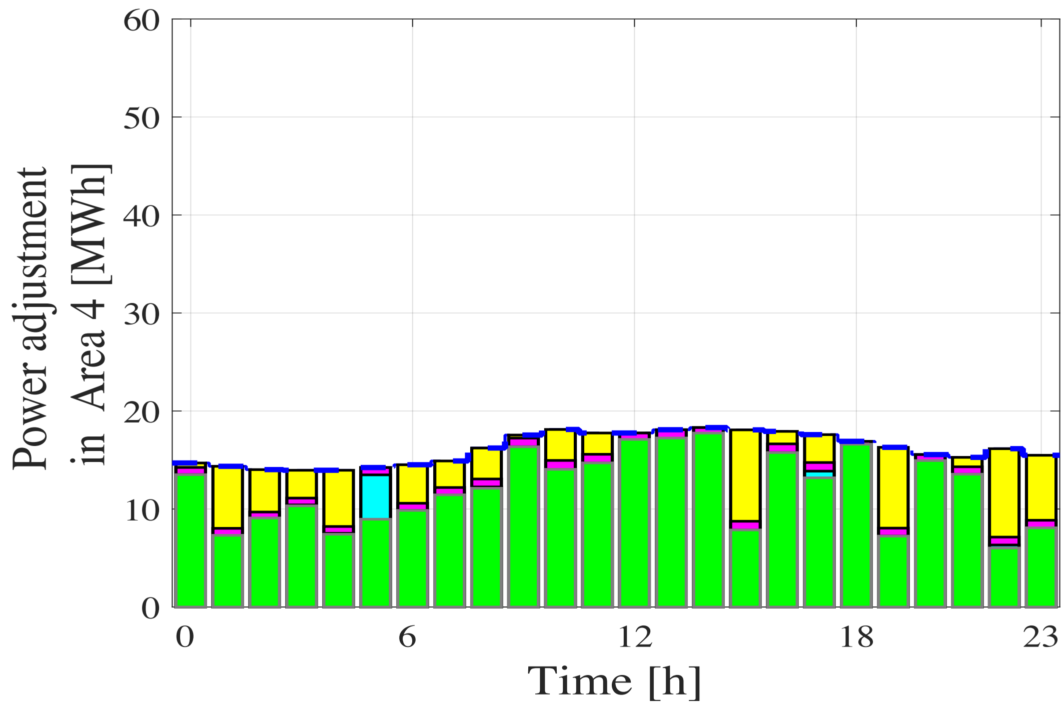

Figure 3-15: Power adjustment in area 4

At each time slot, the generation shortage in each area is covered by a combination of the available resource in such a way that minimize the total cost of the balancing operation. The demand reduction represents the largest portion of the utilized resources followed by the balancing generation. The power flow changes are the least utilized resource for its high cost among the other. However, at sometimes, power flow change could be significantly utilized. For example, the generation shortage in area 3 at 12:00PM is covered by 0.799 MW from balancing generators, 3.82 MW demand reduction, and 2.99 MW imported power from the other areas. These 3 quantiles accounts for the difference between the forecasted and real supplies at that time in area 3, which is 7.62 MW.

3.7 Comparison to Previous Results in Reference [43]

Since the method followed in this chapter relies on previously presented study in [43], this subsection is dedicated to compare the results of both studies. The objective of both studies is minimizing the grid supply-demand balance cost in real time using different resources including balance generators, power flow capabilities among areas/zones, and DR offers via aggregators. However, the followed mechanisms are different for the part of utilizing DR resources (negawatt trading). The negawatt trading in [43] offers a demand reduction dependent incentive pricing, so retailers find the optimum demand reductions that would maximize their profits. As explained previously in this chapter for the ISO-aggregator trading mechanism, the demand reductions offered by aggregators are sold at bulk market electricity prices. The comparison of both methods results will be about the quantities of utilized resources in each area in the system.

3.7.1 Quantities of Resources in area 1

- DR Resources

DR resources using the new method in area 1 is 102.31 MWh, while DR resources for the previous method is 100.01 MWh. The new method achieves 2.3 MWh more DR resources than the previous method. Figures 3-16 and 3-17 show DR resources in area 1 using the new method presented in this chapter and the previous method in [43], respectively.

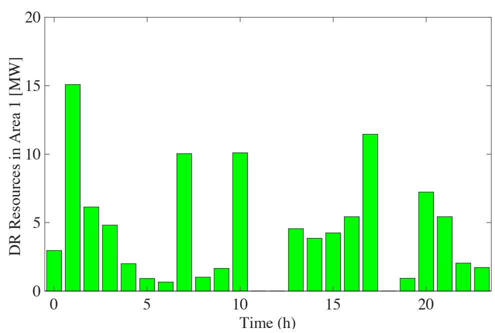

Figure 3-16: DR resources in area 1 from chapter 3

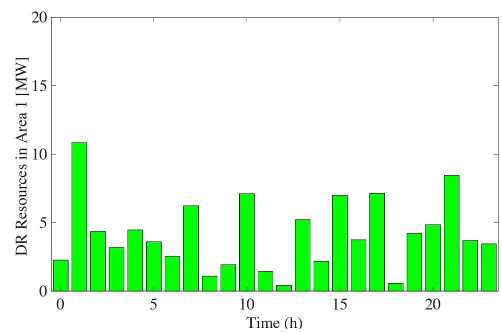

Figure 3-17: DR resources in area 1 from [43]

- Power Flow Exchange

Comparing the two methods in terms of power flow changes, the power flow changes during the entire day in area 1 for the new method in chapter 3 fluctuate between -0.8 MWh and 1 MWh, while the power flow changes during the entire day in area 1 for the previous method fluctuate between -3 MWh and 4 MWh. The method in chapter 3 achieves less fluctuation range for power flow in area 1.

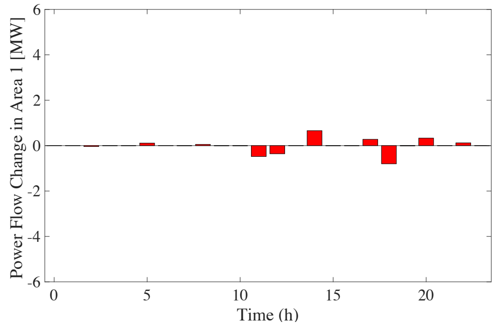

Figure 3-18: Power flow change in area 1 from chapter 3

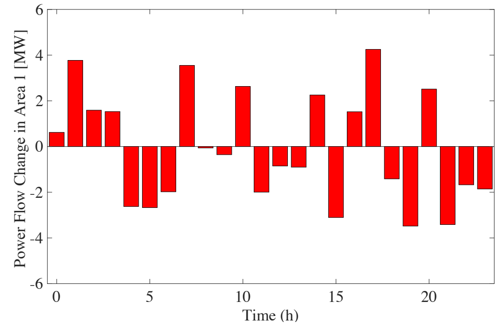

Figure 3-19: Power flow change in area 1 from [43]

- Balance Generation

The new method presented in this chapter achieves lower utilization for the balancing generation in area 3 as compared to the previous work in [43]. To illustrate, the total balancing generation in a 24-hour period at area 1 for the new method is 36.23 MWh, while it was 40.56 MWh using the previous method. Figures 3-20 and 3-21 shows the balancing generation profile in area 1 for the new method presented in this chapter and the previous work in [43], respectively.

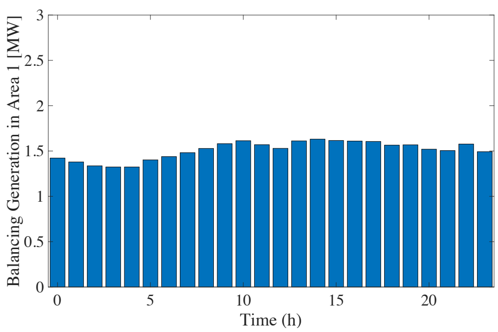

Figure 3-20: Balancing generation in area 1 from chapter 3

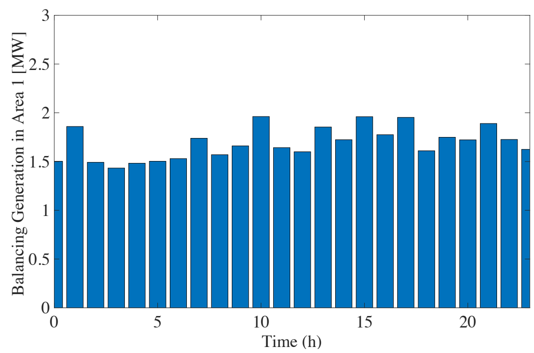

Figure 3-21: Balancing generation in area 1 from [43]

3.7.2 Quantities of Resources in area 2

- DR Resources

DR resources using the new method in area 2 is 125.76 MWh, while DR resources for the previous method is 145.52 MWh. The new method achieves about 20 MWh less DR resources than the previous method. Figures 3-22 and 3-23 show DR resources in area 2 using the new method presented in this chapter and the previous method in [43], respectively.

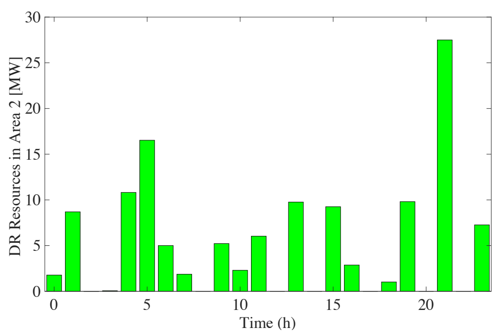

Figure 3-22: DR resources in area 2 from chapter 3

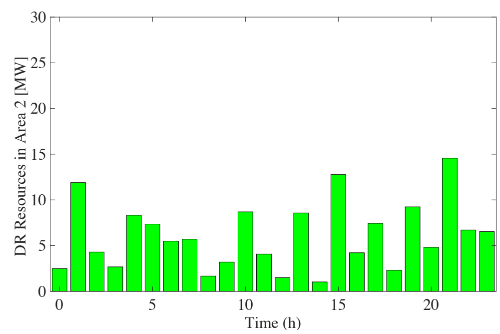

Figure 3-23: DR resources in area 2 from [43]

- Power Flow Exchange

Comparing the two methods in terms of power flow changes, the power flow changes during the entire day in area 2 for the new method in chapter 3 fluctuate between -5 MWh and 1.5 MWh, while the power flow changes during the entire day in area 1 for the previous method fluctuate between -10 MWh and 12.5 MWh. The method in chapter 3 achieves less fluctuation range for power flow in area 2.

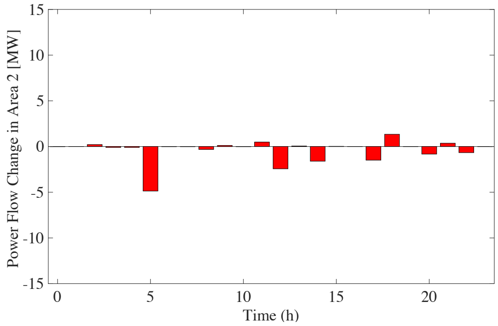

Figure 3-24: Power flow change in area 2 from chapter 3

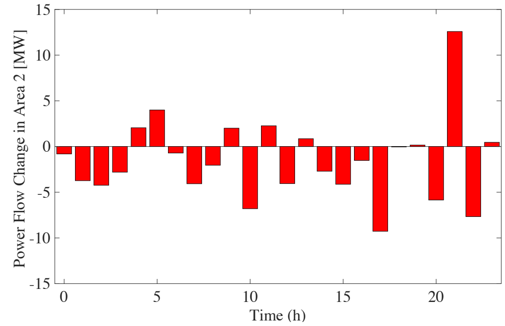

Figure 3-25: Power flow change in area 2 from [43]

- Balance Generation

The new method presented in this chapter achieves lower utilization for the balancing generation in area 2 as compared to the previous work in [43]. To illustrate, the total balancing generation in a 24-hour period at area 2 for the new method is 52.91 MWh, while it was 59.39 MWh using the previous method. Figures 3-26 and 3-27 shows the balancing generation profile in area 2 for the new method presented in this chapter and the previous work in [43], respectively.

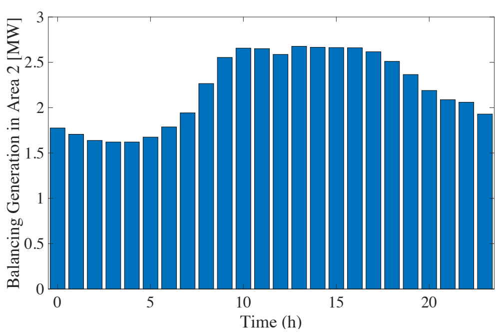

Figure 3-26: Balancing generation in area 2 from chapter 3

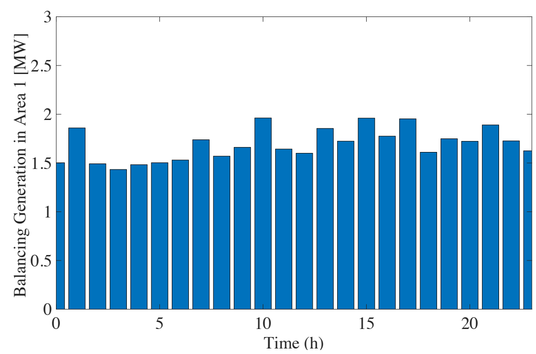

Figure 3-27: Balancing generation in area 1 from [43]

3.7.3 Quantities of Resources in area 3

- DR Resources

DR resources using the new method in area 3 is 68.14 MWh, while DR resources for the previous method is 50.55 MWh. The new method achieves 18 MWh more DR resources than the previous method. Figures 3-28 and 3-29 show DR resources in area 3 using the new method presented in this chapter and the previous method in [43], respectively.

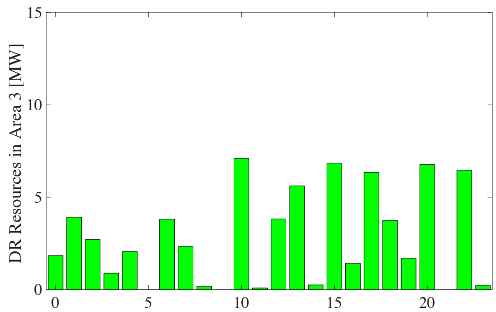

Figure 3-28: DR resources in area 3 from chapter 3

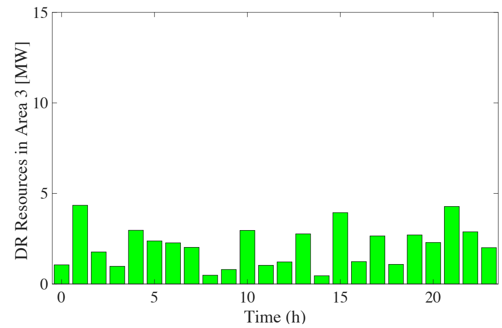

Figure 3-29: DR resources in area 3 from [43]

- Power Flow Exchange

Comparing the two methods in terms of power flow changes, the power flow changes during the entire day in area 3 for the new method in chapter 3 fluctuate between -0.4 MWh and 3.5 MWh, while the power flow changes during the entire day in area 1 for the previous method fluctuate between -5 MWh and 5 MWh. The method in chapter 3 achieves less fluctuation range for power flow in area 1.

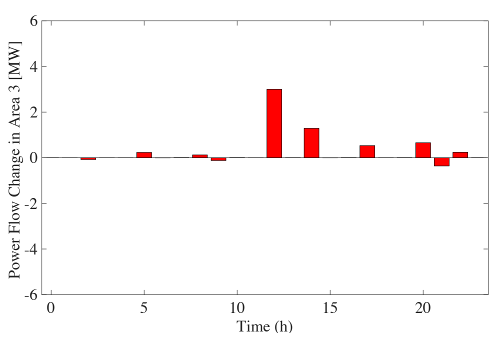

Figure 3-30: Power flow change in area 3 from chapter 3

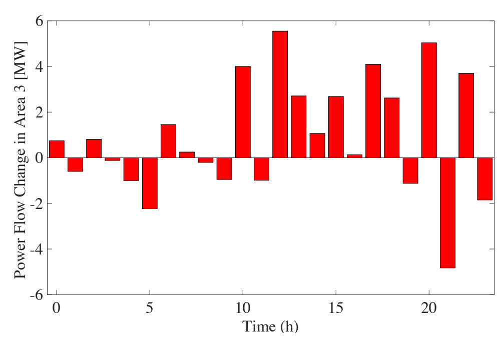

Figure 3-31: Power flow change in area 3 from [43]

- Balance Generation

The new method presented in this chapter achieves lower utilization for the balancing generation in area 3 as compared to the previous work in [43]. To illustrate, the total balancing generation in a 24-hour period at area 3 for the new method is 16.60 MWh, while it was 18.75 MWh using the previous method. Figures 3-32 and 3-33 shows the balancing generation profile in area 3 for the new method presented in this chapter and the previous work in [43], respectively.

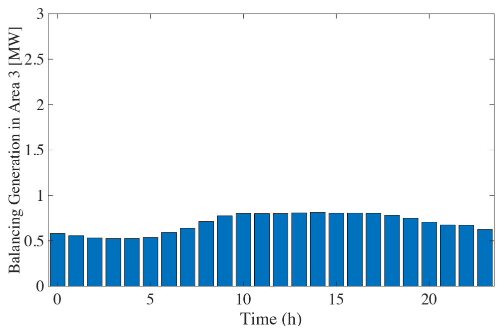

Figure 3-32: Balancing generation in area 3 from chapter 3

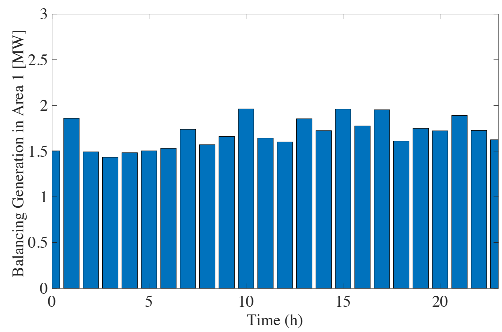

Figure 3-33: Balancing generation in area 1 from [43]

3.7.4 Quantities of Resources in area 4

- DR Resources

DR resources using the new method in area 4 is 73.43 MWh, while DR resources for the previous method is 58.18 MWh. The new method achieves 15 MWh more DR resources than the previous method. Figures 3-34 and 3-35 show DR resources in area 4 using the new method presented in this chapter and the previous method in [43], respectively.

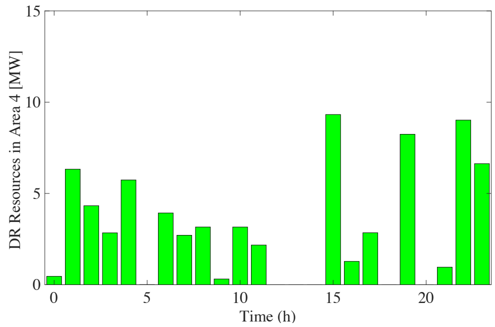

Figure 3-34: DR resources in area 4 from chapter 3

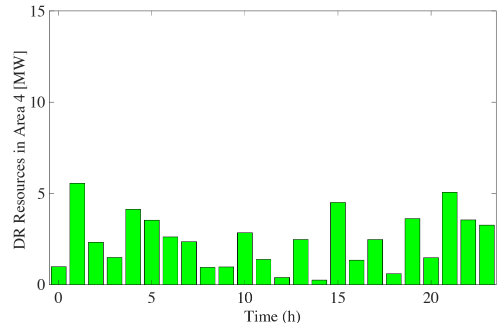

Figure 3-35: DR resources in area 4 from [43]

- Power Flow Exchange

Comparing the two methods in terms of power flow changes, the power flow changes during the entire day in area 4 for the new method in chapter 3 fluctuate between -0.5 MWh and 4.7 MWh, while the power flow changes during the entire day in area 1 for the previous method fluctuate between -4.5 MWh and 5.6 MWh. The method in chapter 3 achieves less fluctuation range for power flow in area 4.

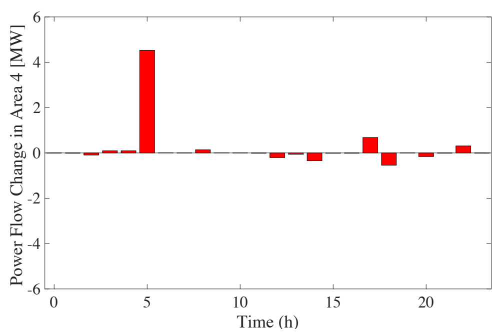

Figure 3-36: Power flow change in area 4 from chapter 3

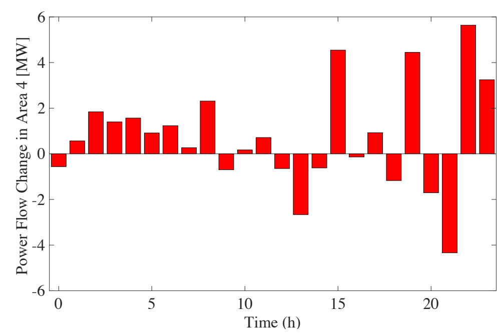

Figure 3-37: Power flow change in area 4 from [43]

- Balance Generation

The new method presented in this chapter achieves lower utilization for the balancing generation in area 4 as compared to the previous work in [43]. To illustrate, the total balancing generation in a 24-hour period at area 4 for the new method is 19.37 MWh, while it was 21.80 MWh using the previous method. Figures 3-38 and 3-39 shows the balancing generation profile in area 4 for the new method presented in this chapter and the previous work in [43], respectively.

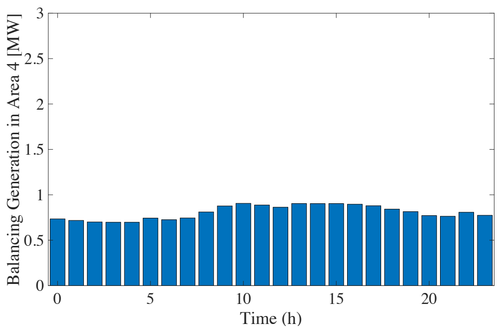

Figure 3-38: Balancing generation in area 4 from chapter 3

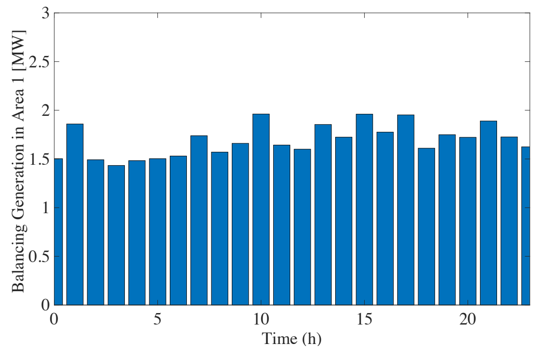

Figure 3-39: Balancing generation in area 4 from [43]

Table 3-1 summarizes the comparison between the method presented in chapter 3 and the method presented in [43] with respect to balancing generation. As the numbers show, the utilization of balancing generation is reduced using the new method presented in this chapter, which is beneficial from different prospective. Form an environment prospective, lowering the production of balancing generator decreases accompanying GHGs emissions due to the fact that balancing generators are mostly fossil-fueled based units [48], [49]. In addition, the need for balancing services affects electricity prices in real time market due to the high-priced bidding of balancing units [50].

Table 3-1: Comparison between the method of chapter and the method in [43] for balancing generation

Area	Balancing Generation from Chapter 3 Method (MWh)	Balancing Generation from Method in [43] (MWh)
1	36.23	40.56
2	52.91	59.39
3	16.60	18.75
4	19.37	21.80

Table 3-2 summarizes the comparison between the method presented in chapter 3 and the method presented in [43] with respect to balancing generation. DR resources prove its practicality in providing ancillary services such as balancing services in our case. Using DR resources is faster in response to unexpected imbalances in the grid than using only balancing generators [51], [52].

Table 3-2: Comparison between the method of chapter and the method in [43] for DR resources

Area	DR Resources from Chapter 3 Method (MWh)	DR Resources from Method in [43] (MWh)
1	102.31	100.01
2	125.76	145.52
3	68.14	50.55
4	73.43	58.18
All	369.6	354.26

In addition, power flow exchanges among areas are used for providing balancing services in both methods. Table 3-3 summarizes the comparison between the method presented in chapter 3 and the method presented in [43] with respect to power flow exchanges among the areas of the system. From a market point of view, net tie-line power flow exchanges between areas must be zero, meaning each area must serve its load by utilizing energy produced within it [53]. Otherwise, there must be a trading mechanism for tie-line power flow among area, which is out of the scope of this chapter. Note that when the net power flow is a negative number, it means that an area exports energy to other areas, and vice versa. In summation, the new method achieves lower fluctuation ranges of tie-line power flow changes among areas.

Table 3-3: Comparison between the method of chapter and the method in [43] for power flow exchanges

Area	**Power Flow Exchange Range from Chapter 3 Method (MWh)**	**Power Flow Exchange Range from Method in [43] (MWh)**
1	[-0.8, 1]	[-3, 4]
2	[-5, 1.5]	[-10, 12.5]
3	[-0.4, 3.5]	[-5, 5]
4	[-0.5, 4.7]	[-4.5, 5.6]

3.8 Conclusion

In this chapter, a relationship between the ISO and DR aggregator is established for the latter to take place in the power supply-demand adjustment operation. The proposed power management method includes not only the demand reductions set to the DR aggregators but also changes in power flows among the power network areas from what scheduled in the day-ahead market. We verify the applicability of our proposed method by applying it to a multiple area power network. The results show distributed resources participating in a real-time marker to balance the demand with the supply. The generation errors caused by uncontrolled variations in renewable energy generators are fixed by balancing generators, power flow changes, and demand reductions to be provided by DR aggregators.

The method in this chapter determines the exact values of load that DR aggregators required to reduce through interacting with individual customers in different areas of the power network. However, the chapter does not address the relationship between the DR aggregator and customers and the method by which the aggregator brings the required demand and sell it to the ISO. This issue will be addressed in chapter 4.

CHAPTER 4

INTEGRATING DR AGGREGATORS WITH CARBON TAXATION

4.1 Overview

This chapter presents a market framework for DR aggregators integrated into electric power transmission system. These load shifting-based aggregators apply resource allocation problem to customer assets and optimize for profit maximization. The chapter also applies carbon taxation for fossil fueled generators in order to reduce carbon dioxide emissions which is one of the major contributors to climate change. The DR market in line with the proposed carbon taxation is simulated on the RBTS test system using PowerWorld. The market framework achieves improvements in the technical performance of power system and electricity markets. It also brings environmental benefits by achieving emissions reduction.

This chapter is a verbatim reproduction of the work accepted and published to a peer-reviewed journal in [54]. As requested by the copyright holder, the published article is listed in the references section. The numbering of the figures and tables has been modified to satisfy the formatting requirements of the dissertation.

4.2 Introduction

The 2007 Energy Independence and Security Act (EISA07) introduced the U.S. Smart Grid Initiative as the grid modernization drive in the U.S. Moving toward the modern smart grid required setting its characteristics by the policy maker. The set characteristics of the U.S. smart grid include integration of demand side resources, DR, renewable resources, and smart appliances and customer devices [55]. The integration of such large amounts of resources into power grid increases the system complexity; however, it would bring a potential to improve the system flexibility to perform in a more efficient and reliable approach.

The U.S. department of energy (DOE) also declared a Smart Grid Initiative to enhance the national electric power system in different aspects including supply reliability, transmission security, and energy efficiency. The DOE modernization strategy includes allowing active participation by end-users through DR programs [56].

The incorporation of demand side resources is implemented through DSM, which includes all operations that control and influence the behavior of energy usage over time. Due to the fact that power systems infrastructure is designed to supply peak demand, DSM is applied mostly for deferral of installing new infrastructure. Investing in new power plants and transmission lines to supply the increasing demand is not efficient due to the large PAR of the load profile. Therefore, the main goal of DSM is to flatten the load profile so that the difference between peak and average demand is reduced [57]. Load shifting technique in DSM is frequently used to transfer as much controllable loads as possible from peak times to other times when demand is lower [58]. This technique reduces peak demands without changing the total amount of energy consumption. Other DSM techniques can achieve the main goal, but they may affect the total energy consumption. These techniques include peak clipping and valley filling. For the peak clipping technique, load is cut at peak times to reduce peak demand. Conversely, the energy consumption is promoted at off-peak times for the valley filling technique.

In addition to reducing peak demand, DSM represents a promising technique in providing balancing services in real-time electricity markets. DSM utilizes distributed energy resources (DERs) and DR as balancing resources for power demand-supply adjustment. These resources provide quick balancing services within 5 mins. This timeframe is shorter than the large-scale conventional generators which typically takes within 15-20 mins [59]. The increasing integration of renewable energy sources (RES) in the generation capacity makes balancing services of high importance to system operators. That importance stems from the unpredictable fluctuations on the supply side due to the involvement of RES.

Due to recent developments in AMI, bidirectional communication between the utilities and consumers can be invested for implementing DR programs [60]. In these programs, consumers are monetarily incentivized to change their energy consumption over time for the system benefit in the form of peak demand reduction or demand-supply adjustment. That leads to other general advantages such as reduction in energy generation cost and GHG emissions.

The danger of anthropogenic climate change is dire, and international efforts are required to alleviate or possibly eliminate its menacing effects [61]. Electricity production is among the largest sources of GHG emissions in the United State. The emissions come from burning fossil fuels, mainly coal and natural gas [62]. Due to the extreme difficulty of quantifying the exact costs of climate change causes, policies can be set to reduce emissions by designing appropriate pricing for emissions [63]. The major two approaches to price emissions are taxation on GHG emissions and a cap-and-trade system [64], [65]. The taxation system sets a direct price for GHG emissions in order to implicitly encourage emissions reduction, while the cap-and-trade system explicitly sets an annual limit for GHG emissions in the form of tradable allowances and pricing is determined by the equilibrium of supply and demand. The revenues collected from these taxation systems could be designed for investing in green generation technologies or for supporting alternative sectors by reducing their tax rates.

The applications of DR programs in the industry sector are already applied by system operators. Nevertheless, applying DR programs in the residential sector is challenging for the system operator due mainly to the small power ratings of residential consumers. The participation of residential customers can be applied via a DR aggregator which act as a mediator between the consumers and the system operator. In [18], an aggregator-based resource allocation technique is presented for profit maximization. A heuristic optimization framework is proposed to find an optimal reschedule for controllable appliances in a large-scale system.

In this chapter, analyzing the effects of the SGRA technique on the day-ahead electricity market in a multi-area network is conducted. We also apply an emission rate-based carbon tax for fossil-fueled based power plants. Along with integrating DR aggregators, we apply the proposed taxation to fossil-fueled generators and quantify its environmental and economic impacts. The main contributions of this chapter are as follows:

- Analyzing the effects of multiple SGRA aggregators in the network on the power system performance.
- Quantify the reduction in total cost of production by the integration of aggregators.
- Designing a framework for DRX in the day-ahead market.
- Introducing carbon taxation and assessing its applicability for the environment and the electricity market economics.

The work in this chapter is aimed to study the effects of multiple SGRA-based aggregators on the electricity market along with a carbon taxation levied fossil-fueled power plants. The rest of the chapter is organized as follows: Section 4.3 presents the system model and problem formulation. Section 4.4 presents the study results and section 4.5 concludes this chapter and mentions some potential future work.

4.3 System Model and Problem Formulation

The SGRA approach for residential-based aggregators proves its feasibility in making profits as a primary objective. Moreover, it simultaneously realizes peak demand shaving as it shifts controllable appliances away from that period and sell aggregate demand reduction to the

ISO. The effects of integrating more than an aggregator in interconnected areas of the network is required. Therefore, we evaluate the performance of the power network in terms of efficiency and reliability. We also design a DRX market framework for multiple aggregators in the network to provide demand reductions at peak times. Along with peak demand reductions provided by DR aggregators, we design a carbon tax for fossil-fuel based generators and measure its influence on GHG emissions.

4.3.1 System Model

For the assessment of multiple aggregators' effects in the electric grid and electricity market, we need a fully defined test system for simulation. We use the RBTS test system for simulating the electricity market [66]. As shown in figure 4-1, RBTS is a 6-bus system with 9 transmission lines. It contains 11 generators with a maximum capacity of 240 MW and nominal load of 185 MW. The generators are classified into different categories based on their served load: base load, intermediate load, and peak load units. The RBTS has been divided into two areas connected through 3 lines as shown in figure 4-1. The two 5-MW generators of the RBTS generators are classified as peak units. So, The RBTS has been modified by moving a 5-MW generator from bus 2 to bus 1 to be assigned a peak unit in area 1.

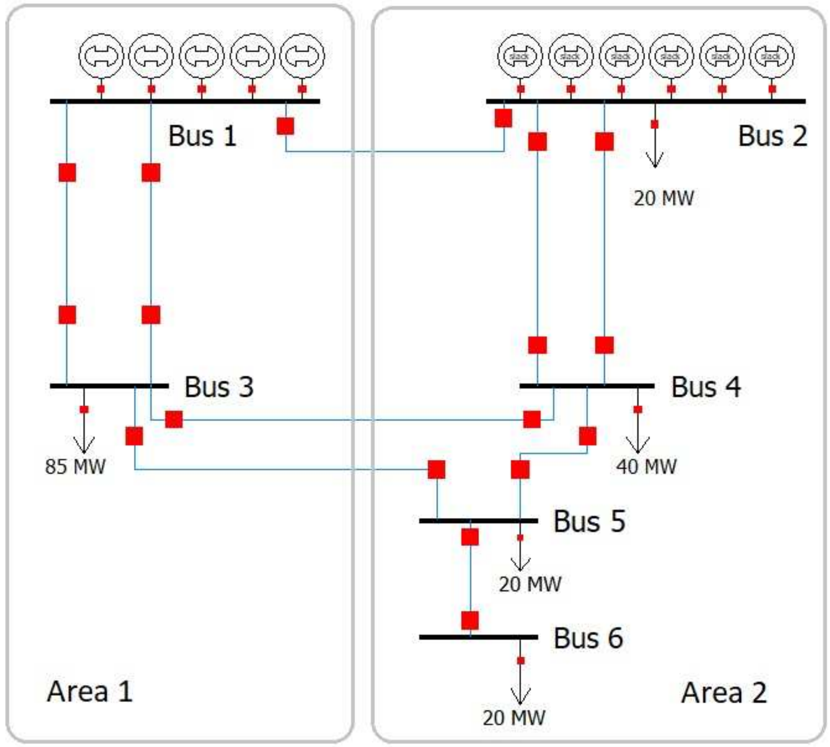

Figure 4-1: Modified RBTS system divided into two areas

The generation profile of the RBTS has been set to mimic the PJM generation profile [67]. Each generator' cost function is defined according to its classification. The first derivative of the generator cost function represents the marginal cost function which equates the marginal price of the generator [68]. Table 4-1 shows the data of the RBTS generators.

Table 4-1: RBTS generators data

Area	Generator No.	Classification	Type	Capacity (MW)	Marginal Cost Function ($/MWh)
1	1	base load	coal (C)	40	$\frac{dC_1(P_1)}{dP_1} = 0.0146P_1+15.52$
	2	base load	nuclear	40	$\frac{dC_2(P_2)}{dP_2} = 0.0146P_2+15.52$
	3	intermediate	hydro	20	$\frac{dC_3(P_3)}{dP_3} = 0.0026P_3+62.41$
	4	intermediate	natural gas-combined cycle (CC)	10	$\frac{dC_4(P_4)}{dP_4} = 0.0026P_4+62.41$
	5	peak	natural gas (NG)	5	$\frac{dC_5(P_5)}{dP_5} = 0.0064P_5+183.32$
2	6	base load	nuclear	40	$\frac{dC_6(P_6)}{dP_6} = 0.0146P_6+15.52$
	7	base load	coal (C)	20	$\frac{dC_7(P_7)}{dP_7} = 0.0146P_7+15.52$
	8	base load	coal (C)	20	$\frac{dC_8(P_8)}{dP_8} = 0.0146P_8+15.52$
	9	intermediate	hydro	20	$\frac{dC_9(P_9)}{dP_9} = 0.0026P_9+62.41$
	10	intermediate	natural gas-combined cycle (CC)	20	$\frac{dC_{10}(P_{10})}{dP_{10}} = 0.0026P_{10}+62.41$
	11	peak	natural gas (NG)	5	$\frac{dC_{11}(P_{11})}{dP_{11}} = 0.0064P_{11}+183.32$

Real load data of PJM system from July 1, 2019 is used to represent the load profile of the RBTS for a 24-h period [69]. Table 4-2 shows the load values of PJM transmission region organization.

Table 4-2: RBTS generators data

Time	Load (MW)
0:00	83226.27
1:00	78121.46
2:00	74692.65
3:00	72712.71
4:00	72592.70
5:00	74883.31
6:00	79241.70
7:00	85817.55
8:00	91656.88
9:00	96988.52
10:00	103038.40
11:00	108168.50
12:00	112856.80
13:00	117384.90
14:00	121751.90
15:00	125513.80
16:00	128866.80
17:00	130760.90
18:00	130247.40
19:00	126721.20
20:00	120961.30
21:00	116215.40
22:00	107884.80
23:00	98419.92

The PJM load is scaled down to fit the nominal load values at each load bus b of the RBTS system for each hour h, L_h^b, according to (1).

$$L_h^b = \alpha_A \, L_{nom}^b \, \frac{L_h^{PJM}}{L_{peak}^{PJM}} \qquad (1)$$

where L_h^{PJM} is the total load of PJM at each hour h, L_{peak}^{PJM} is the peak maximum load of the PJM system on that day, L_{nom}^b is the nominal load of bus b on the RBTS system, and $\alpha_A$is a scaling factor for each area A which used to adjust the scaled RBTS loads to the need for the entire generation units in each area including peak units [70]. Not to exceed the maximum generation capacity and to ensure convergence of the system optimal power flow (OPF), $\alpha_1$and α_2 are empirically set to be 1.3 and 1.2 respectively.

After defining the generation and load characteristics of the RBTS system, we run the system under OPF to find the operating levels of the power plants in each area. The OPF is a major tool for ISO power markets and is solved in different times for different purposes to ensure supplying the system load with lowest generation costs possible in a secure and efficient mode [71]. Figure 4-2 and figure 4-3 show the operating levels of the generators for a 24-h period under OPF in area 1 and 2 respectively. For the same interval, a locational marginal price (LMP) is also determined at each bus of both areas which reflects the marginal cost value of the marginal generator at each hour. Figure 4-4 shows the spot market prices (i.e., the LMPs), at buses 2-6.

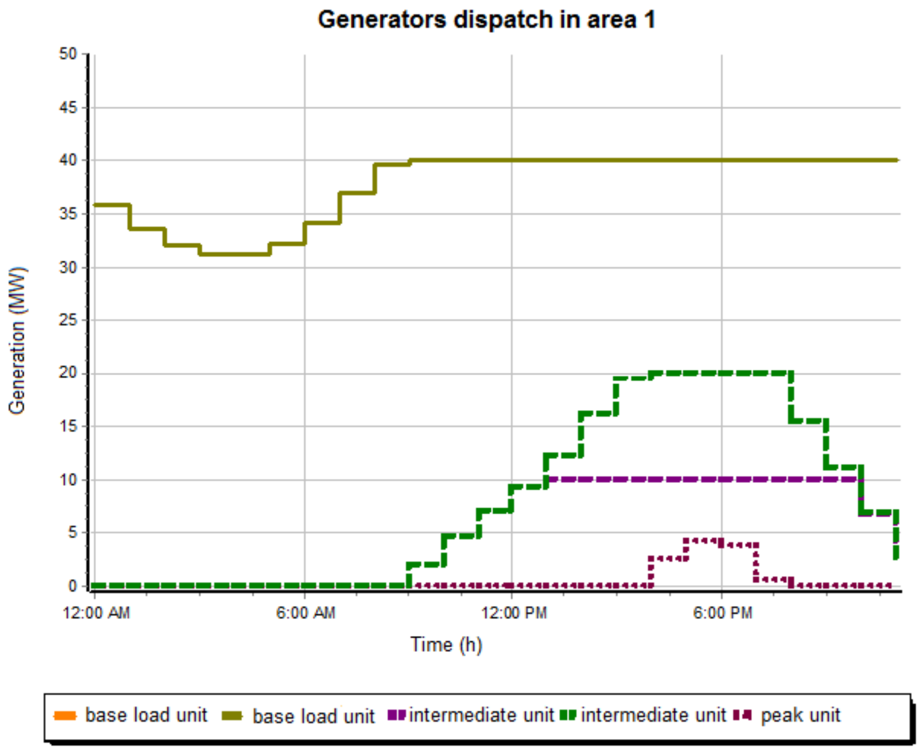

Figure 4-2: Generation dispatch in area 1

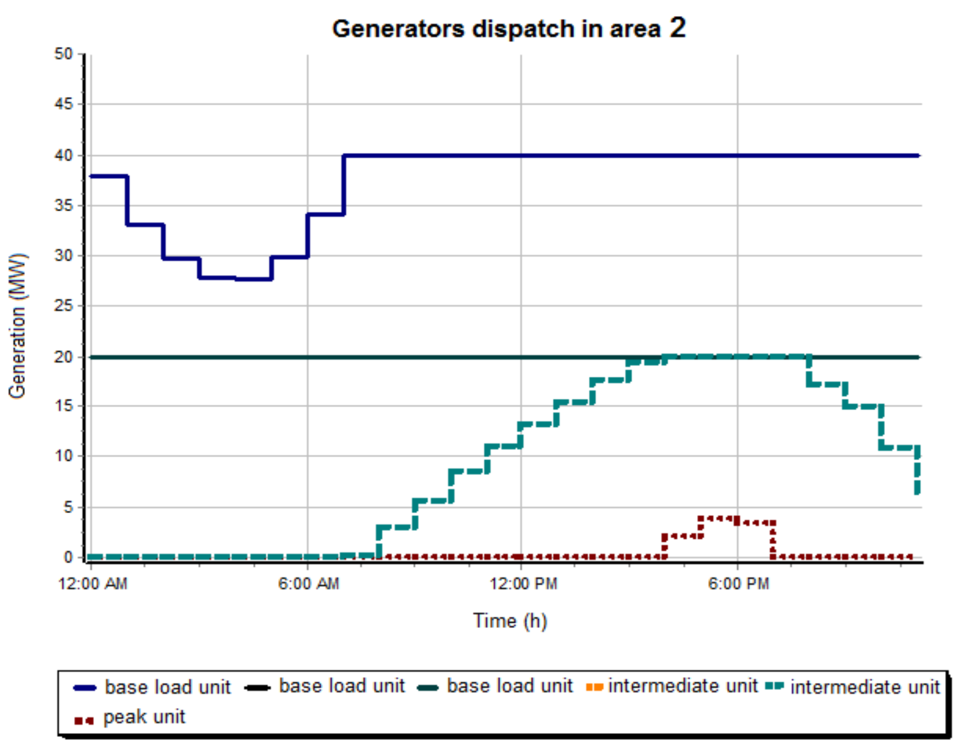

Figure 4-3: Generation dispatch in area 2

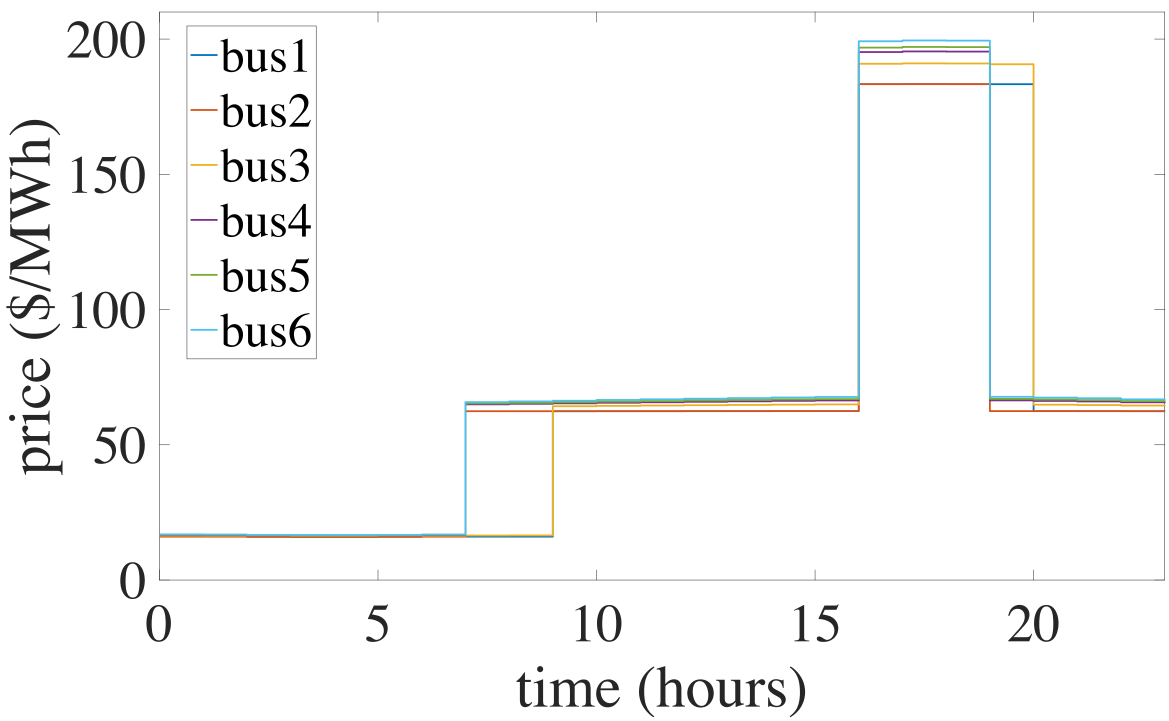

Figure 4-4: Locational marginal prices at the system buses

4.3.2 Problem Formulation

We apply the SGRA aggregation approach to each load in the RBTS system. Each load represents a distribution system run by a local utility to supply its customers. As presented in [18], the aggregator runs in parallel with the utility and should offer CIP lower than the utility pricing in order to compensate the customers for the rescheduling inconvenience. The simulation of the SGRA problem uses the LMPs determined at each bus as a spot market price. As for the utility pricing, we synthetically design different types of pricing for each aggregator as presented in table 4-3.

Table 4-3: RBTS generators data

area#	bus#	pricing
1	3	RTP
2	2	TOU pricing
2	4	fixed tariff pricing
2	5	RTP
2	6	TOU pricing

We design a market framework managing the trade between the ISO and the multiple aggregators in the system in a day-ahead time frame. The aggregators provide demand reductions for sale to the ISO at high priced peak times so as to maximize their profits. To create a competition environment among the participating aggregators, we design a demand-supply market model for DRX as follows:

- The ISO determines the required peak demand reduction at each hour during peak period
- The Aggregators offer prices for demand reductions at peak hours
- The ISO accepts the lower priced offers that satisfy the needed reduction
- The unaccepted offers are considered extra marginal resources
- The aggregators are in competition with the peak units

Based on a previous study to find the optimal carbon price for a 2.5 ℃ increase limit, the carbon price is found to be \$25 per metric ton of CO_2 in 2015 with 5% increase annually [72]. Based on the same study, the carbon price is \$30 per metric ton of CO_2 in 2020, which is the price we consider for this study. We apply a carbon tax, $T(E)$, for fossil-fueled generators based on their emission rates of CO_2 per MWh generated according to (2)

$$T(E) = 30\ y^{1.05}\ E \qquad (2)$$

where E is the emission rate in (metric ton CO_2/MWh), and y is an index of annual growth for 30 years {0, 1, 2…30}. Figure 4-5 shows the carbon tax per MWh from 2020 to 2050.

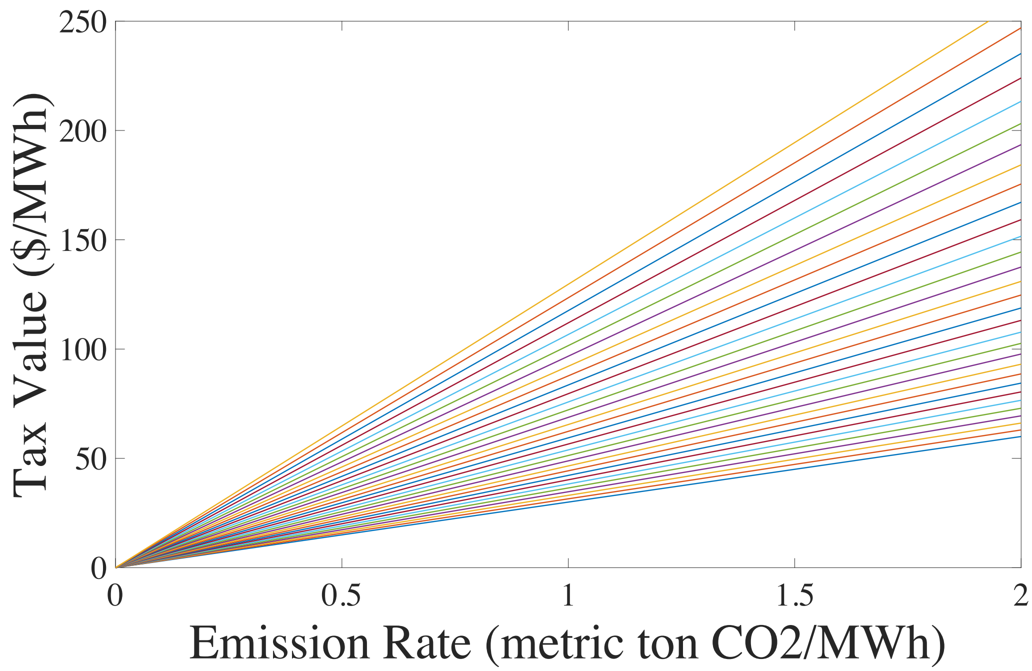

Figure 4-5: Locational marginal prices at the system buses

The levied tax added to the total cost function of a fossil-fueled power plant as in (3).

$$C(P) = aP^2 + (b + T)P + c \qquad (3)$$

where P is active power output of power plant in (MW), a, b and c are coefficient of the quadratic term, coefficient of the linear term, and constant cost respectively, T is carbon tax in ($/MWh). The marginal cost function of the power plant is found by taking the first derivative of the total cost function (4).

$$\frac{dC(P)}{dP} = 2aP + (b + T) \qquad (4)$$

Derived from (8), the tax addition directly increases the marginal price of that power plant, which makes fossil-fueled-based power plants less competitive with other power plants. That will affect the production of fossil-fueled power plants. To illustrate, levying the carbon tax rate is to encourage less production which in return would reduce the amount of CO_2 emissions. The CO_2 emission reduction of a generator in a day is calculated using (5).

$$E_{reduced} = \sum_{h=0}^{24} \left[(G_h^{untaxed} - G_h^{taxed}) \times E \right] \qquad (5)$$

where $E_{reduced}$ is CO_2 emissions reduced during a 24-hour period in (metric tons), $G_h^{untaxed}$ is the energy produced by a generator in hour h before taxation, G_h^{taxed} is the energy produced by a generator in hour h after taxation. The tax revenue collected from a power plant in a day is calculated according to (5).

$$R_{tax} = \sum_{h=0}^{24} \left[G_h^{taxed} \times T(E) \right] \qquad (5)$$

4.4 Results

The carbon tax is imposed on fossil-fueled generators according to (2) based on their emission rates. Table 4-4 shows CO_2 emission rates of major types of fossil-fueled power plants [73]. The carbon tax levied on each one of them is also shown in Table 4-4. The imposed carbon tax is added to the total production costs of the fossil-fueled generator in the RBTS system in both areas. That directly increases the marginal costs of these generators. As a result, the LMPs at the buses of the system are changed accordingly as shown in figure 4-6.

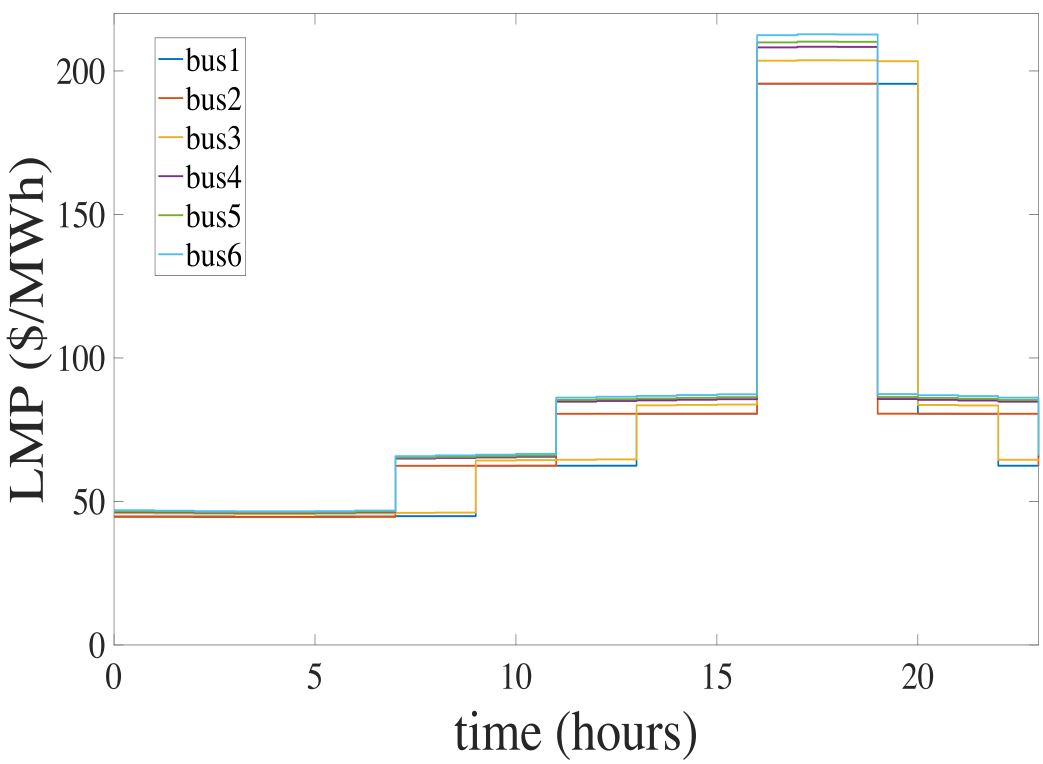

Figure 4-6: Locational marginal prices after imposing taxation

Table 4-4: Emissions rates of fossil-fueled generators [73]

Generator Type	Emission Rate (metric ton CO_2/ MWh)	Carbon Tax ($/MWh)
Coal	0.961	28.83
Petroleum	0.743	22.29
Natural Gas	0.604	18.12
Natural Gas-Combined Cycle	0.407	12.21

Based on the new pricing with carbon taxation, each aggregator at a load bus of the system autonomously finds a schedule for a set of participating controllable assets and a CIP in its zone (i.e. its bus). We show the outputs of the five integrated aggregators in the system. We show the outputs of aggregators 2-6 including the customer incentive pricing and the controllable assets load profile as follow:

Aggregator 2

Figure 4-7 shows the spot market prices, the utility prices, and the CIP of the aggregator at bus 2. The load of the schedulable assets before and after performing the SGRA approach at bus 2 is shown in figure 4-8. The aggregator shifts a part of the schedulable load from peak to other times during the day achieving peak demand reduction. Figure 4-9 shows the total load at bus 2 before and after integrating aggregator 2. The SGRA based aggregation performed by only the aggregator at bus 2 would achieve a total peak demand reduction in area 2 from 120 MW to 115.78 MW at 5:00 PM. This also reduce the PAR of the load profile at area 2 due to the peak demand reduction with keeping the energy consumption fixed during the day. This also decreases the utilization factor of the peaking unit in area 2. It exactly reduces its production from 9.17 MWh to

2.15 MWh in the entire day. The total cost of production of the peaking unit at area 2 is also reduced in correspondence to its production reduction. The total cost in the entire day is reduced from $1777 to $489.85

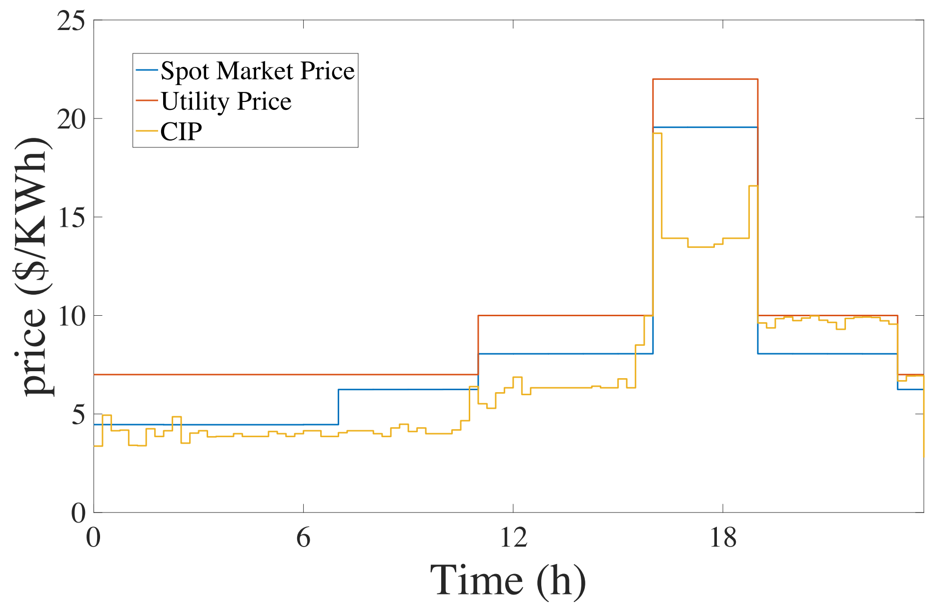

Figure 4-7: Spot market price, utility price, and CIP of the aggregator at bus 2

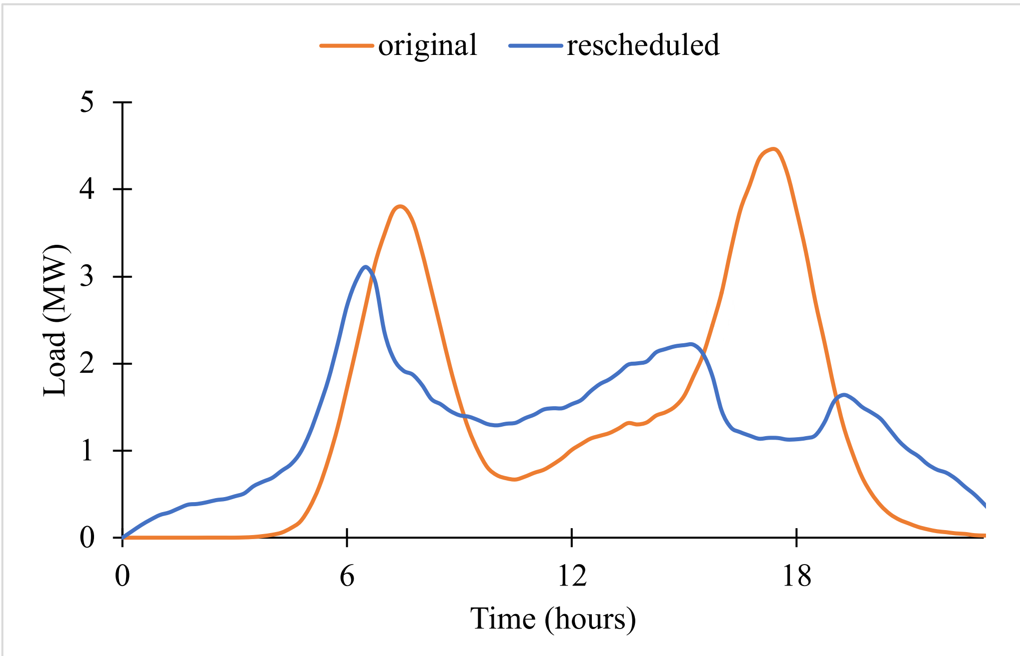

Figure 4-8: Original and rescheduled controllable load participating with the aggregator at bus 2

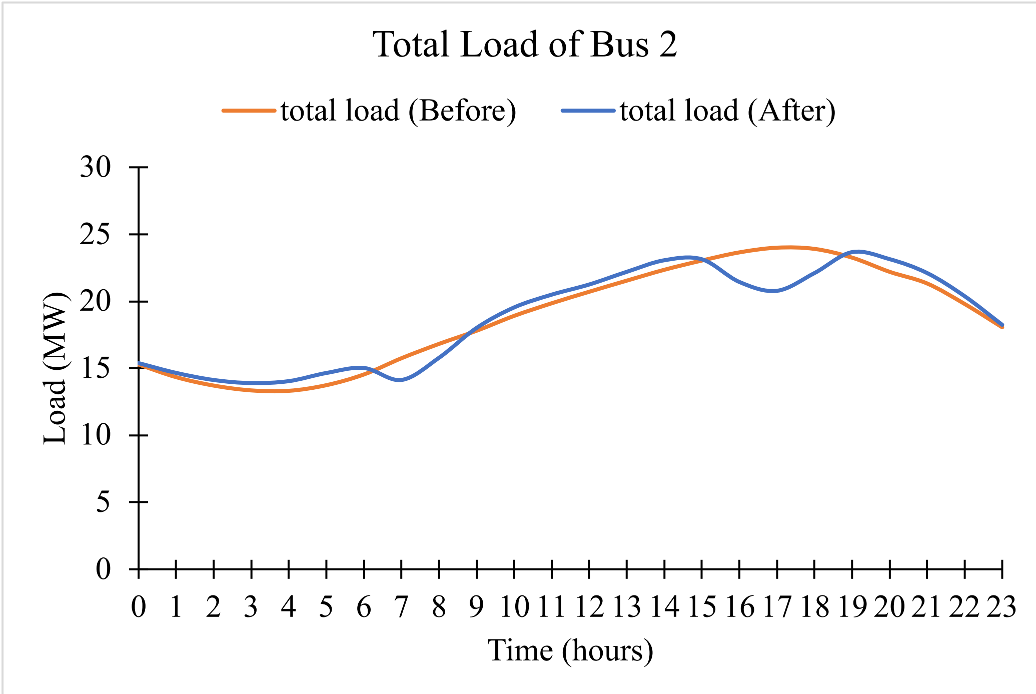

Figure 4-9: Total load at bus 2 before and after integrating aggregator 2

Table 4-5 compares the nodal prices at bus 2 for the 24-h period before and after the integration of aggregator 2 at bus 2 in area 2.

Table 4-5: Nodal prices at bus 2 before and after integrating an aggregator

Time	Price Before Aggregation ($/MWh)	Price After Aggregation ($/MWh)
12:00:00 AM	44.61	44.61
1:00:00 AM	44.61	44.61
2:00:00 AM	44.55	44.55
3:00:00 AM	44.55	44.55
4:00:00 AM	44.55	44.55
5:00:00 AM	44.55	44.55
6:00:00 AM	44.61	44.61
7:00:00 AM	62.42	44.61
8:00:00 AM	62.43	62.43
9:00:00 AM	62.44	62.44
10:00:00 AM	62.46	62.46
11:00:00 AM	80.54	80.54
12:00:00 PM	80.55	80.55
1:00:00 PM	80.56	80.56
2:00:00 PM	80.57	80.57
3:00:00 PM	80.58	80.58
4:00:00 PM	195.54	80.58
5:00:00 PM	195.55	195.53
6:00:00 PM	195.55	195.54
7:00:00 PM	80.58	195.53
8:00:00 PM	80.57	80.57
9:00:00 PM	80.56	80.56
10:00:00 PM	80.54	80.54
11:00:00 PM	62.45	62.45

Aggregator 3

Figure 4-10 shows the spot market prices, the utility prices, and the CIP of the aggregator at bus 3. The load of the schedulable assets before and after performing the SGRA approach at bus 3 is shown in figure 4-11. The aggregator shifts a part of the schedulable load from peak to other times during the day achieving peak demand reduction. Figure 4-12 shows the total load at bus 2 before and after integrating aggregator 3. The SGRA based aggregation performed by only the aggregator at bus 3 would achieve a total peak demand reduction in area 2 from 110.5 MW to 107.34 MW at 5:00 PM. This also reduce the PAR of the load profile at area 1 due to the peak demand reduction with keeping the energy consumption fixed during the day. This also decreases the utilization factor of the peaking unit in area `. It exactly reduces its production from 11.1 MWh to 3.77 MWh in the entire day. The total cost of production of the peaking unit at area 2 is also reduced in correspondence to its production reduction. The total cost in the entire day is reduced from \$2131 to \$786.8

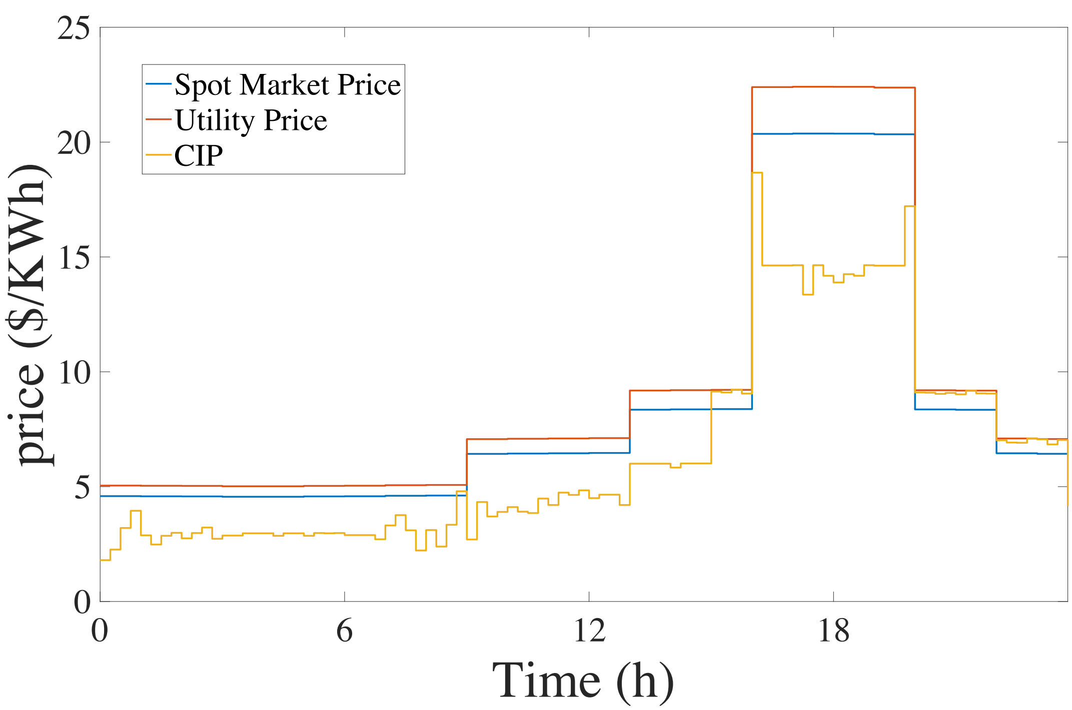

Figure 4-10: Spot market price, utility price, and CIP of the aggregator at bus 3

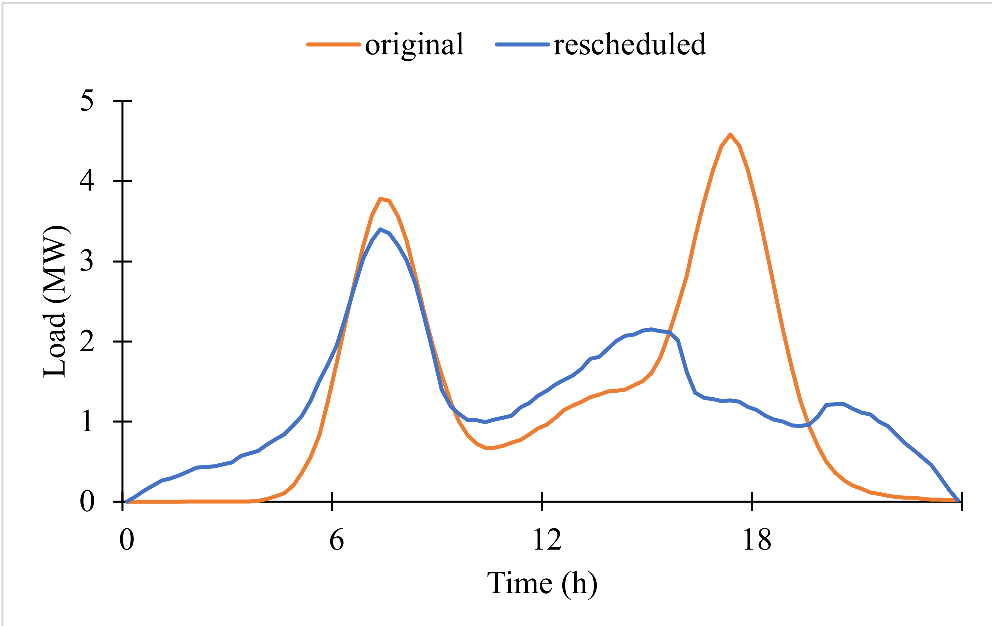

Figure 4-11: Original and rescheduled controllable load participating with the aggregator at bus 3

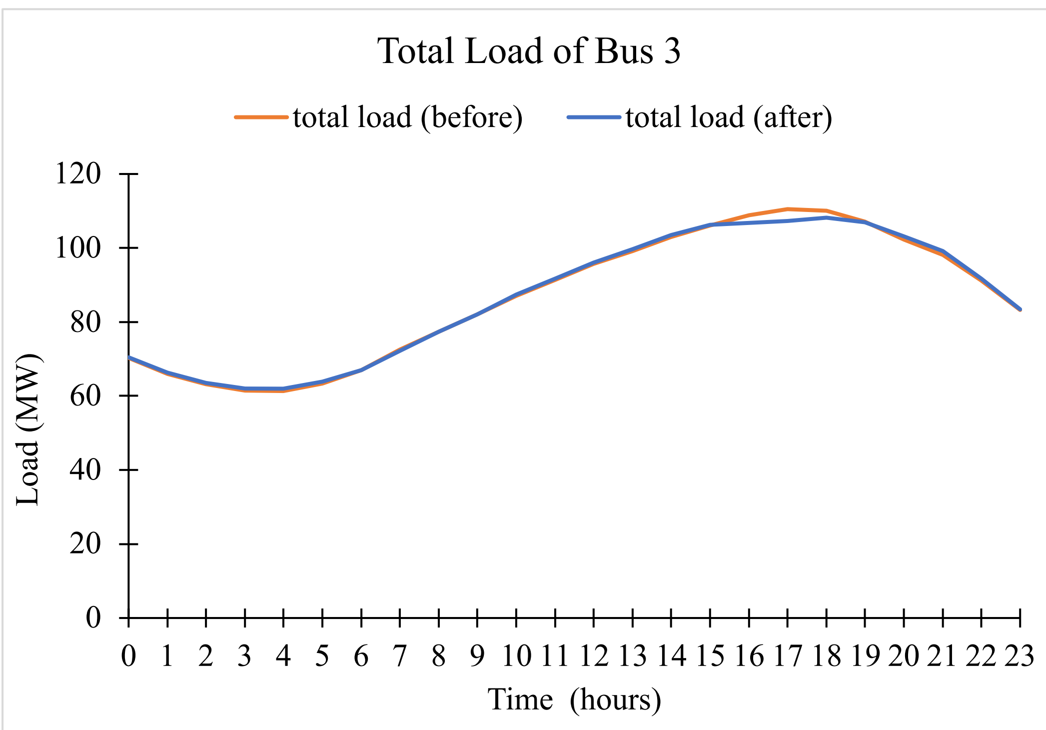

Figure 4-12: Total load at bus 3 before and after integrating aggregator 3

Table 4-6 compares the nodal prices at bus 3 for the 24-h period before and after the integration of aggregator 3 at bus 3 in area 1.

Table 4-6: Nodal prices at bus 3 before and after integrating an aggregator

Time	Price Before Aggregation ($/MWh)	Price After Aggregation ($/MWh)
12:00:00 AM	45.87	45.88
1:00:00 AM	45.8	45.8
2:00:00 AM	45.75	45.76
3:00:00 AM	45.6	45.61
4:00:00 AM	45.6	45.61
5:00:00 AM	45.75	45.76
6:00:00 AM	45.82	45.82
7:00:00 AM	46.03	46.03
8:00:00 AM	46.12	46.12
9:00:00 AM	64.26	64.26
10:00:00 AM	64.41	64.42
11:00:00 AM	64.53	64.54
12:00:00 PM	64.66	64.67
1:00:00 PM	83.5	83.51
2:00:00 PM	83.64	83.66
3:00:00 PM	83.76	83.76
4:00:00 PM	203.58	203.41
5:00:00 PM	203.73	203.48
6:00:00 PM	203.69	203.54
7:00:00 PM	203.4	203.39
8:00:00 PM	83.61	83.64
9:00:00 PM	83.46	83.49
10:00:00 PM	64.53	64.54
11:00:00 PM	64.3	64.3

Aggregator 4

Figure 4-13 shows the spot market prices, the utility prices, and the CIP of the aggregator at bus 4. The load of the schedulable assets before and after performing the SGRA approach at bus 4 is shown in figure 4-14. The aggregator shifts a part of the schedulable load from peak to other times during the day achieving peak demand reduction. Figure 4-15 shows the total load at bus 2 before and after integrating aggregator 4. The SGRA based aggregation performed by only the aggregator at bus 4 would achieve a total peak demand reduction in area 2 from 120 MW to 116.97 MW at 5:00 PM. This also reduce the PAR of the load profile at area 2 due to the peak demand reduction with keeping the energy consumption fixed during the day. This also decreases the utilization factor of the peaking unit in area 2. It exactly reduces its production from 9.17 MWh to 2.44 MWh in the entire day. The total cost of production of the peaking unit at area 2 is also reduced in correspondence to its production reduction. The total cost in the entire day is reduced from $1777 to $543

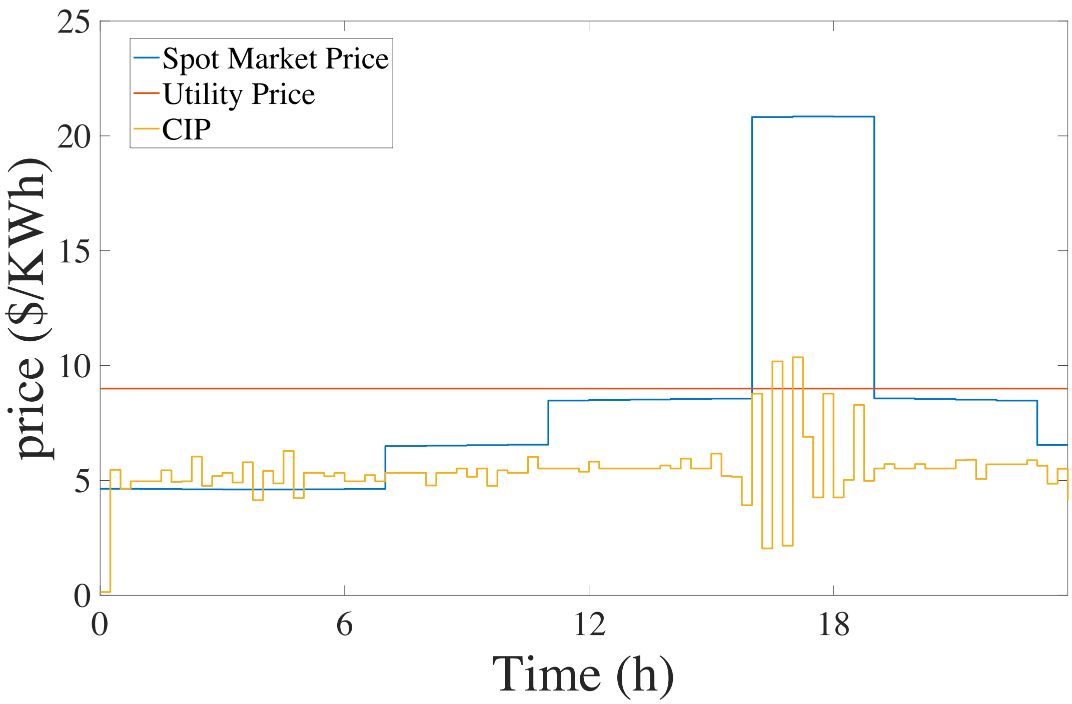

Figure 4-13: Spot market price, utility price, and CIP of the aggregator at bus 4

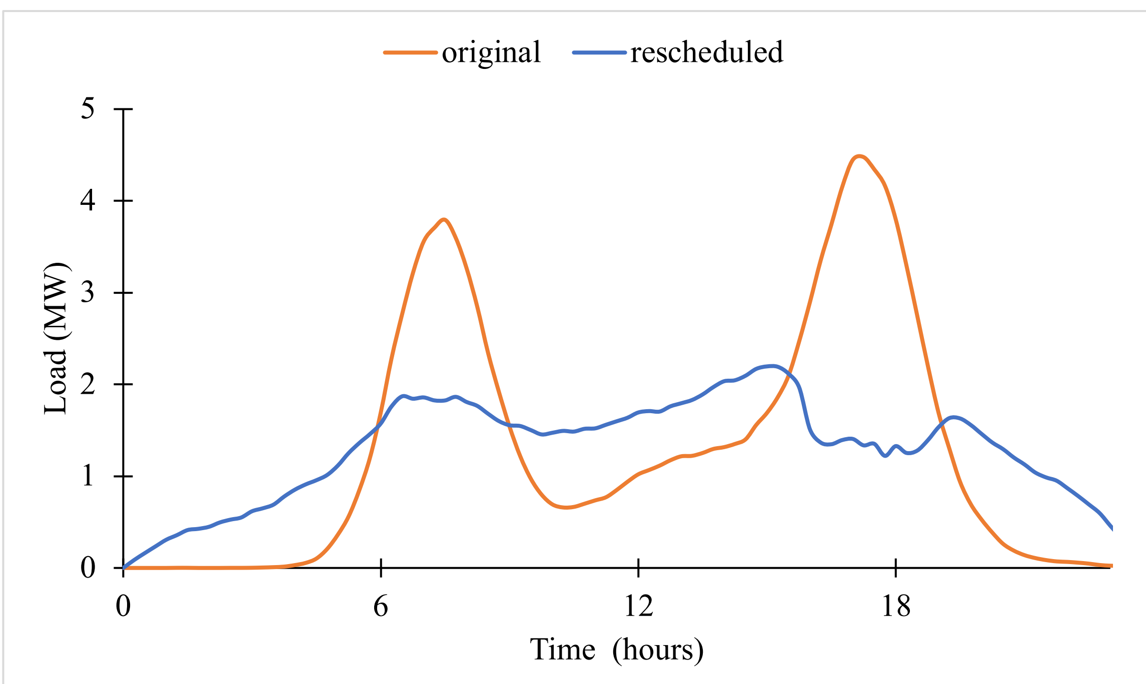

Figure 4-14: Original and rescheduled controllable load participating with the aggregator at bus 4

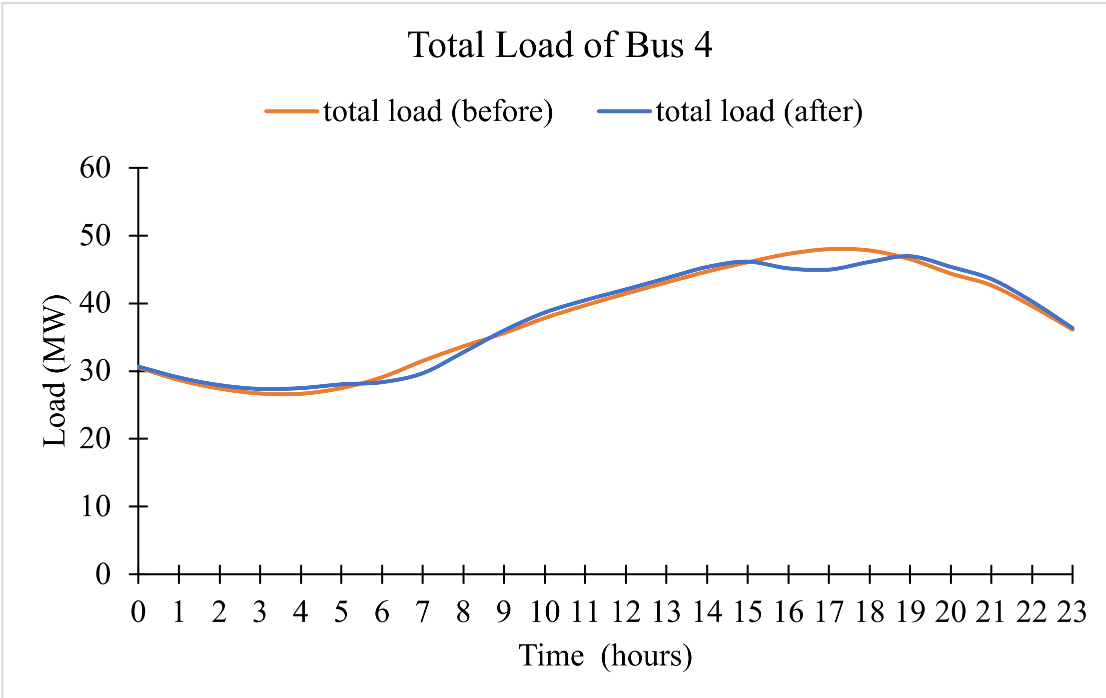

Figure 4-15: Total load at bus 4 before and after integrating aggregator 4

Table 4-7 compares the nodal prices at bus 4 for the 24-h period before and after the integration of aggregator 4 at bus 4 in area 2.

Table 4-7: Nodal prices at bus 4 before and after integrating an aggregator

Time	Price Before Aggregation ($/MWh)	Price After Aggregation ($/MWh)
12:00:00 AM	46.37	46.37
1:00:00 AM	46.25	46.26
2:00:00 AM	46.11	46.13
3:00:00 AM	46.07	46.09
4:00:00 AM	46.07	46.09
5:00:00 AM	46.12	46.13
6:00:00 AM	46.28	46.26
7:00:00 AM	64.95	46.38
8:00:00 AM	65.16	65.12
9:00:00 AM	65.34	65.36
10:00:00 AM	65.57	65.61
11:00:00 AM	84.78	84.82
12:00:00 PM	85.01	85.04
1:00:00 PM	85.22	85.26
2:00:00 PM	85.44	85.48
3:00:00 PM	85.63	85.64
4:00:00 PM	208.21	85.67
5:00:00 PM	208.44	207.99
6:00:00 PM	208.38	208.12
7:00:00 PM	85.69	208.01
8:00:00 PM	85.4	85.46
9:00:00 PM	85.17	85.23
10:00:00 PM	84.77	84.81
11:00:00 PM	65.4	65.41

Aggregator 5

Figure 4-16 shows the spot market prices, the utility prices, and the CIP of the aggregator at bus 5. The load of the schedulable assets before and after performing the SGRA approach at bus 5 is shown in figure 4-17. The aggregator shifts a part of the schedulable load from peak to other times during the day achieving peak demand reduction. Figure 4-18 shows the total load at bus 2 before and after integrating aggregator 5. The SGRA based aggregation performed by only the aggregator at bus 5 would achieve a total peak demand reduction in area 2 from 120 MW to 117.73 MW at 5:00 PM. This also reduce the PAR of the load profile at area 2 due to the peak demand reduction with keeping the energy consumption fixed during the day. This also decreases the utilization factor of the peaking unit in area 2. It exactly reduces its production from 9.17 MWh to 2.12 MWh in the entire day. The total cost of production of the peaking unit at area 2 is also reduced in correspondence to its production reduction. The total cost in the entire day is reduced from $1777 to $484.35

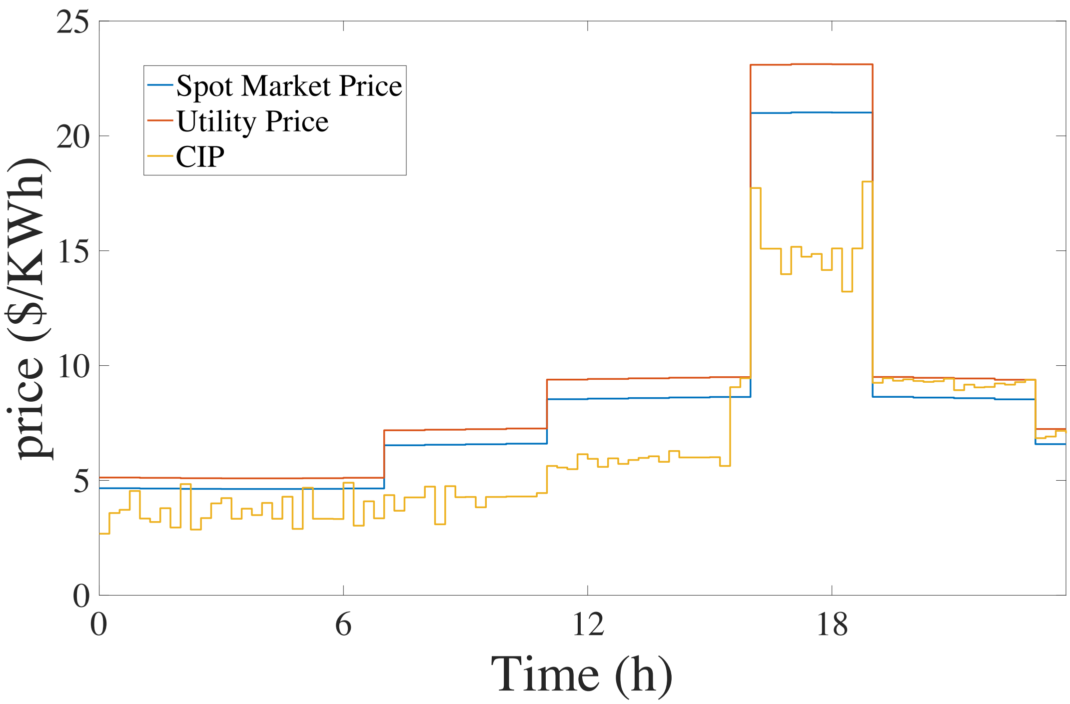

Figure 4-16: Spot market price, utility price, and CIP of the aggregator at bus 5

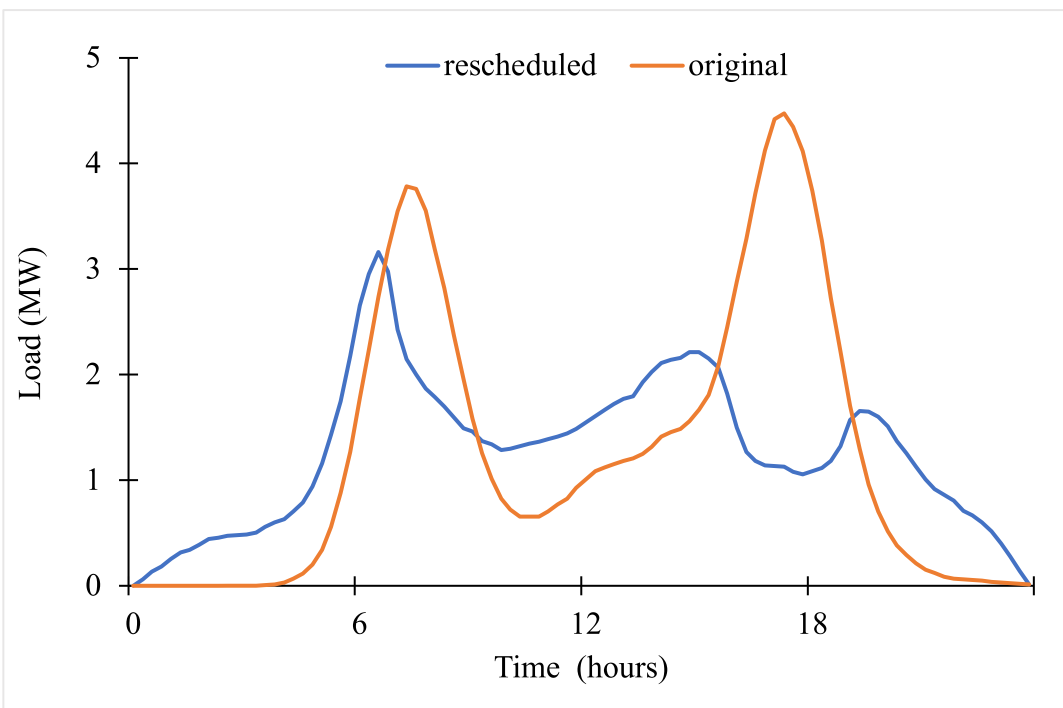

Figure 4-17: Original and rescheduled controllable load participating with the aggregator at bus 5

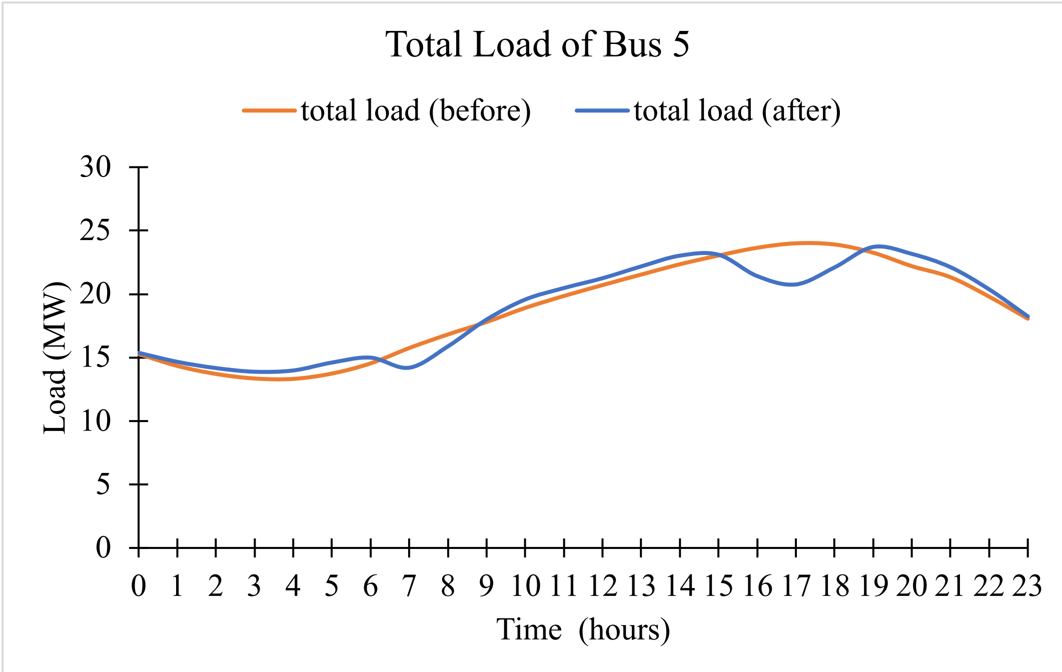

Figure 4-18: Total load at bus 5 before and after integrating aggregator 5

Table 4-8 compares the nodal prices at bus 5 for the 24-h period before and after the integration of aggregator 5 at bus 5 in area 2.

Table 4-8: Nodal prices at bus 5 before and after integrating an aggregator

Time	Price Before Aggregation ($/MWh)	Price After Aggregation ($/MWh)
12:00:00 AM	46.6	46.61
1:00:00 AM	46.47	46.48
2:00:00 AM	46.32	46.34
3:00:00 AM	46.27	46.29
4:00:00 AM	46.27	46.29
5:00:00 AM	46.33	46.36
6:00:00 AM	46.5	46.52
7:00:00 AM	65.3	46.62
8:00:00 AM	65.53	65.48
9:00:00 AM	65.74	65.75
10:00:00 AM	66	66.03
11:00:00 AM	85.36	85.4
12:00:00 PM	85.62	85.65
1:00:00 PM	85.86	85.91
2:00:00 PM	86.11	86.16
3:00:00 PM	86.33	86.33
4:00:00 PM	209.95	86.35
5:00:00 PM	210.22	209.6
6:00:00 PM	210.15	209.8
7:00:00 PM	86.39	209.73
8:00:00 PM	86.07	86.14
9:00:00 PM	85.8	85.86
10:00:00 PM	85.34	85.38
11:00:00 PM	65.8	65.81

Aggregator 6

Figure 4-19 shows the spot market prices, the utility prices, and the CIP of the aggregator at bus 6. The load of the schedulable assets before and after performing the SGRA approach at bus 6 is shown in figure 4-20. The aggregator shifts a part of the schedulable load from peak to other times during the day achieving peak demand reduction. Figure 4-21 shows the total load at bus 2 before and after integrating aggregator 6. The SGRA based aggregation performed by only the aggregator at bus 6 would achieve a total peak demand reduction in area 2 from 120 MW to 116.8 MW at 5:00 PM. This also reduce the PAR of the load profile at area 2 due to the peak demand reduction with keeping the energy consumption fixed during the day. This also decreases the utilization factor of the peaking unit in area 2. It exactly reduces its production from 9.17 MWh to 2.15 MWh in the entire day. The total cost of production of the peaking unit at area 2 is also reduced in correspondence to its production reduction. The total cost in the entire day is reduced from $1777 to $489.8.

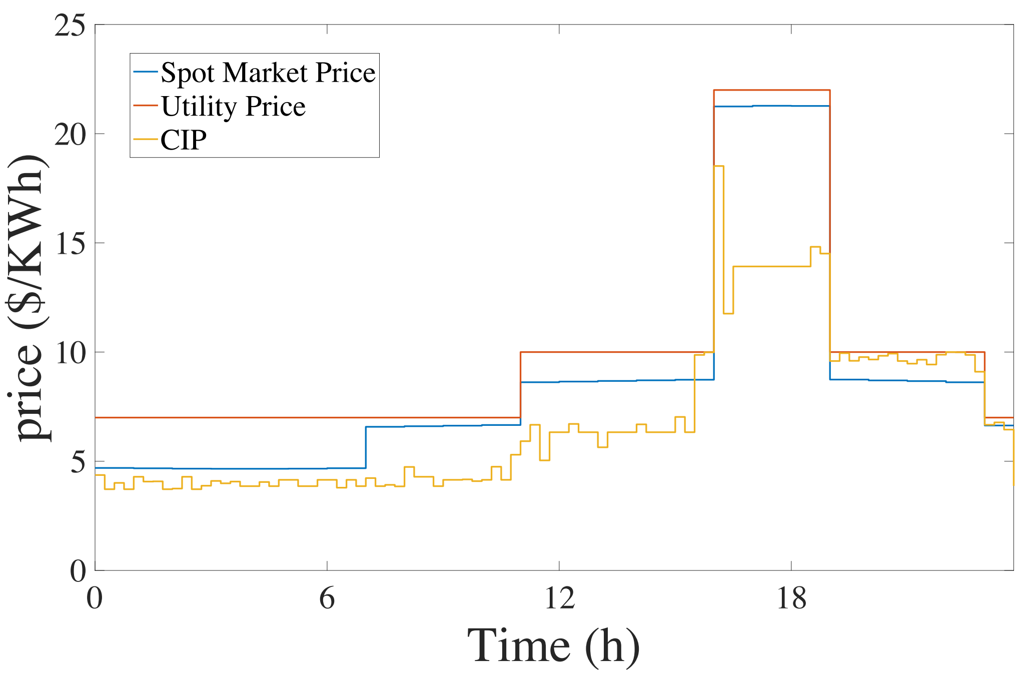

Figure 4-19: Spot market price, utility price, and CIP of the aggregator at bus 6

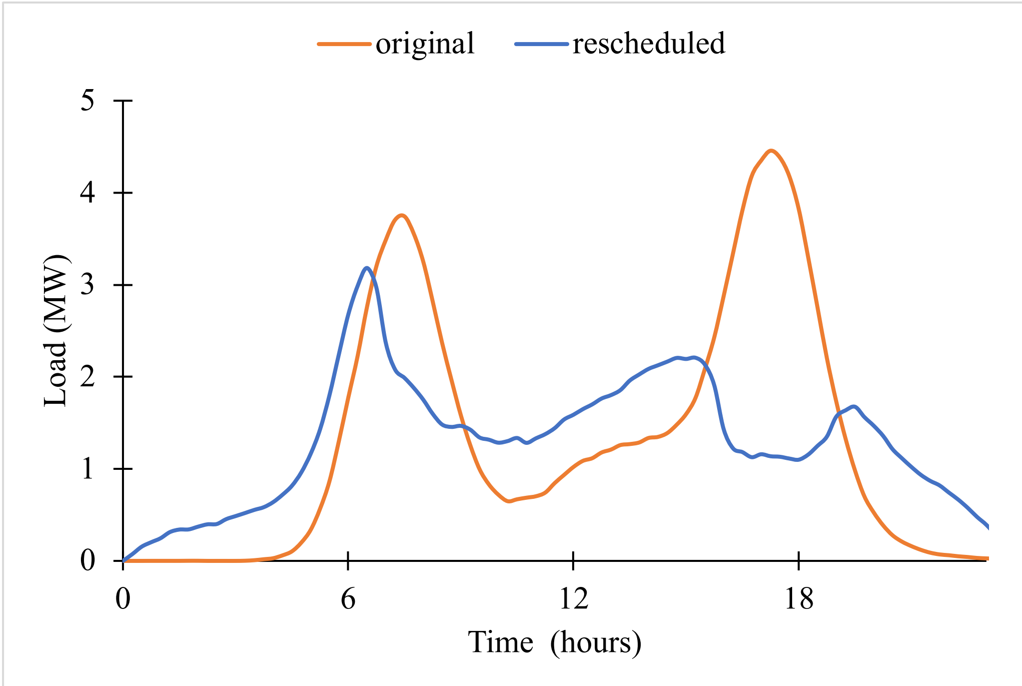

Figure 4-20: Original and rescheduled controllable load participating with the aggregator at bus 6

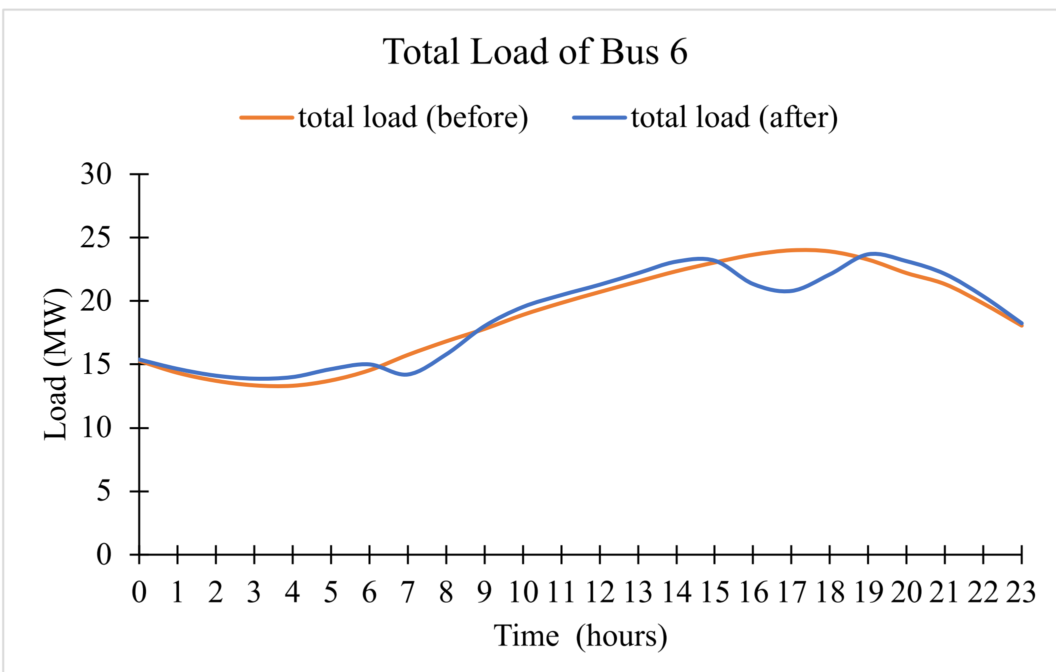

Figure 4-21: Total load at bus 6 before and after integrating aggregator 6

Table 4-9 compares the nodal prices at bus 6 for the 24-h period before and after the integration of aggregator 6 at bus 6 in area 2.

Table 4-9: Nodal prices at bus 6 before and after integrating an aggregator

Time	Price Before Aggregation ($/MWh)	Price After Aggregation ($/MWh)
12:00:00 AM	46.94	46.94
1:00:00 AM	46.78	46.79
2:00:00 AM	46.62	46.63
3:00:00 AM	46.56	46.58
4:00:00 AM	46.56	46.58
5:00:00 AM	46.62	46.64
6:00:00 AM	46.82	46.8
7:00:00 AM	65.78	46.97
8:00:00 AM	66.05	66.02
9:00:00 AM	66.3	66.32
10:00:00 AM	66.6	66.63
11:00:00 AM	86.19	86.23
12:00:00 PM	86.49	86.52
1:00:00 PM	86.78	86.81
2:00:00 PM	87.07	87.11
3:00:00 PM	87.33	87.33
4:00:00 PM	212.46	87.43
5:00:00 PM	212.78	212.35
6:00:00 PM	212.7	212.45
7:00:00 PM	87.41	212.17
8:00:00 PM	87.02	87.07
9:00:00 PM	86.71	86.76
10:00:00 PM	86.17	86.2
11:00:00 PM	66.38	66.38

Reducing the peak demand increases the reliability of the system because it reduces the peaking unit dispatch resulting in larger spinning reserve capacity. More aggregators integrated at different load points in the system brings more peak demand reduction availability which prompts competition among them.

Now that every aggregator at buses 2, 3, 4, 5 and 6 independently achieve peak demand reductions by applying the SGRA approach. These aggregators participate in the DRX market as explained earlier as new market in the timeframe of the day-ahead market. They compete with the peak units for providing peak services as reduction or generation during all peak hours. Peak demands, which are portions of the system load supplied by peak units, are presented in table 4-10. In the DRX market, the ISO asks the available aggregators to bids prices for providing demand reduction. From Table 4-10, the total peak demand of the system is 8.1 MW at 5:00 PM. So, the ISO ask for 8.1 MW reduction from the aggregators. Table 4-11 shows the aggregators bids at 5:00 PM for selling demand reductions. Basically, the ISO accepts the bids with lower prices to the point that fulfills the peak demand need, 8.1 MW in this case. So, the bids of aggregators 4 and 2 are fully accepted, while the bid of aggregator 3 is partially accepted and represents the marginal aggregator. Figure 4-22 shows the aggregators bids for providing peak demand reductions at 5:00PM. As normally determined in electricity markets, the price is determined based upon the marginal cost of producing an extra unit of output. In our case, the electricity spot market price at 5:00 PM is $180 which is the bid price of aggregator 3 as a marginal aggregator.

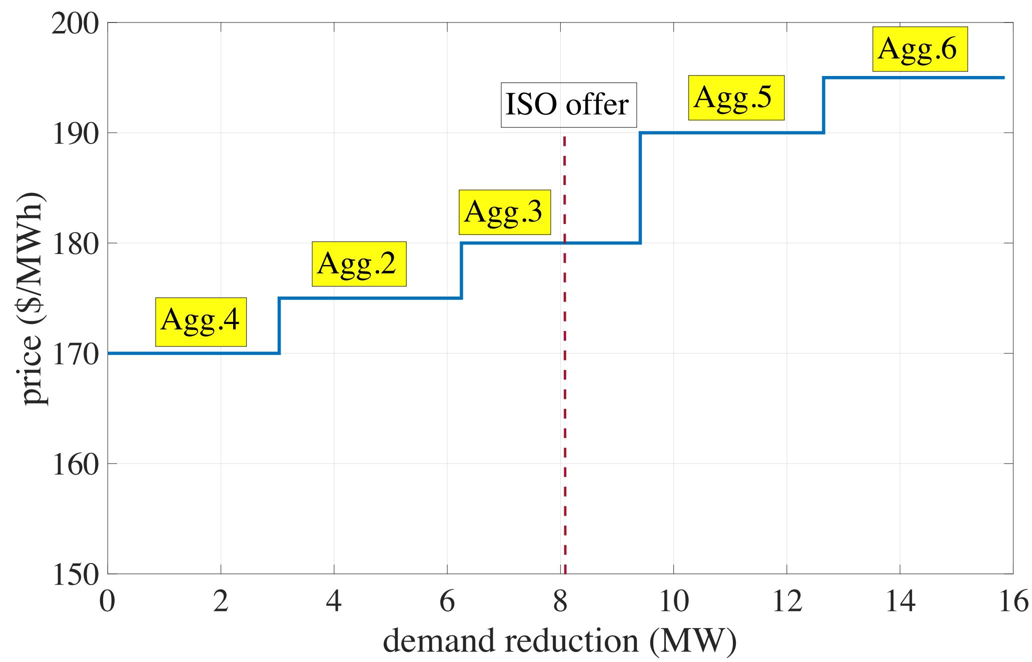

Figure 4-22: Aggregators bids for demand reductions at 5:00PM

Table 4-10: Demand at peak hours

Time (h)	Peak Demand at Area 1 (MW)	Peak Demand at Area 2 (MW)	Total Peak Demand (MW)
4:00PM	2.49	2	4.49
5:00PM	4.24	3.86	8.1
6:00PM	3.79	3.31	7.1
7:00PM	0.58	0	0.58

Table 4-11: Aggregators bids at 5:00PM

bidder	demand reduction (MW)	price ($/MWh)
aggregator 2	3.22	175
aggregator 3	3.16	180
aggregator 4	3.03	170
aggregator 5	3.24	190
aggregator 6	3.20	195

With the availability of peak demand reductions via aggregators, the dispatch of peaking units is reduced accordingly. That reduces the peak period electricity prices since the aggregators can bid with lower prices and still make profits. The carbon taxes imposed on fossil fueled power plants make them less competitive with other types of generators including nuclear and hydro power plants. This leads to reduction in coal and natural gas-based generation and increase in other types of generation in both areas of the system.

Imposing carbon taxes increases the marginal cost function (MCF) of the fossil-fueled generators per (3), thus increasing the respective LMPs at the system buses. Here, the simulations indicate mean electricity price (MEP) increases in areas 1 and 2 of 25% (from 66.4 $/MWh to 83 $/MWh) and 24% (from 67.1 $/MWh to 83 $/MWh), respectively, after imposing $T(E)$. achieving peak demand reductions by aggregators 2-6, which here account for a decrease in the capacity factors (CFs) of the peaking units in areas 1 and 2 by 85% and 73%, respectively, indicated by the simulations. Lowering the CFs of the high cost peaking units by SGRA reduces the MEP increase to 9% (from 66.4 $/MWh to 72.2 $/MWh) in area 1 and 6% (from 67.1 $/MWh to 71 $/MWh) in area 2. Reducing the increase in MEPs is the major significance of applying the SGRA approach with the carbon tax.

Table 4-12 and Table 4-13 show the generation of the fossil-fueled units and their corresponding CO_2 emissions for a 24-hour period in both areas with different cases including the original case with normal OPF only, with applying taxation only, with applying the SGRA approach only, and with combining the SGRA approach and taxation. The results show reductions in production by fossil-fueled generators as they become less competitive with other types of generators after imposing the carbon tax. The dispatch of base load serving nuclear units increases (907 to 960 MWh and 900 to 960 MWh in areas 1 and 2, respectively) to accommodate the corresponding changes from Table 4-12. Nuclear units, while traditionally treated as inflexible, are capable of flexible dispatch [74]. Combining the SGRA with the carbon tax does not achieve lower CO_2 emissions than applying the carbon tax only; however, the addition of the SGRA is beneficial for reducing the spikes in the MEP resulting from applying the carbon tax only.

Note that these values correspond to results from simulations using test data for a random day in a test system mimicking a real-world example. We do not generalize the results; rather, we present a generalized framework for use in any system. All data relevant to this study are given in reference [75].

Table 4-12: Dispatch data of fossil-fueled generators

Area	Generator type	Dispatch (MWh)			
		Original	With tax only	With SGRA only	With tax and SGRA
1	C	907	854	909	859
	CC	122	64	124	66
	NG	11	11	1.6	1.6
	Total	1040	929	1034.6	926.6
2	C	960	900	960	919.5
	CC	222	158	216	148
	NG	9	9	2.5	2.5
	Total	1191	1067	1178.5	1070

Table 4-13: Emission reduction of fossil-fueled generators in 24-hour period

Area	Generator type	CO_2 emissions (metric-ton)			
		Original	With tax only	With SGRA only	With tax and SGRA
1	C	872	821	874	825
	CC	50	26	50	27
	NG	7	7	1	1
	Total	928	853	925	853
2	C	923	865	923	884
	CC	90.5	64	88	60
	NG	5.5	5.5	1.5	1.5
	Total	1019	934.5	1012.5	945.5

Figure 4-23, Figure 4-24, Figure 4-25, and Figure 4-26 show the daily dispatches using different methods of C generators, CC generators, NG generators, and all fossil-fuel generators in area 1, respectively. The involved methods include the original method which represents performing OPF without performing any additional approach. They also include the original method with imposing tax only, the original method with performing SGRA only, and the original method with both imposing taxes and performing SGRA aggregation.

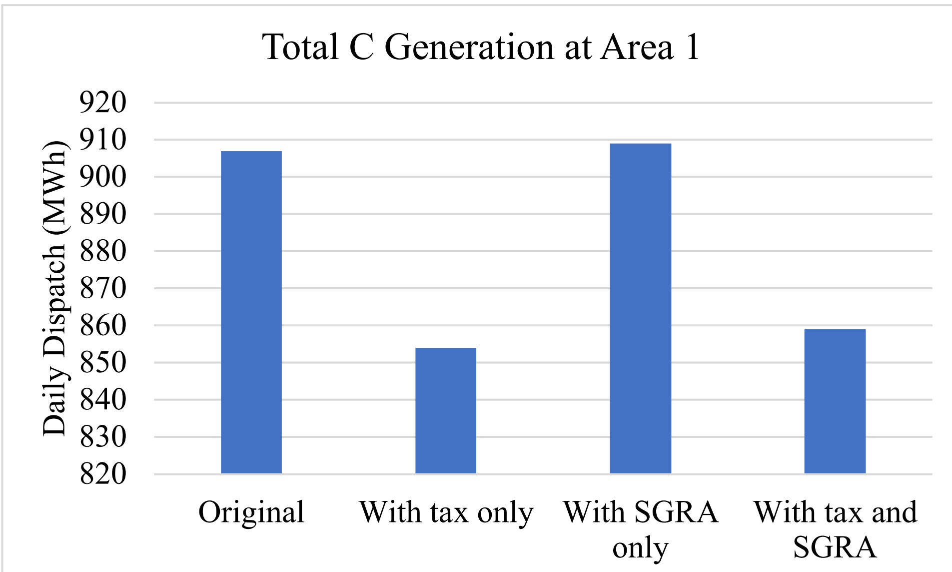

Figure 4-23: Comparison of coal generation dispatches in area 1 using different methods

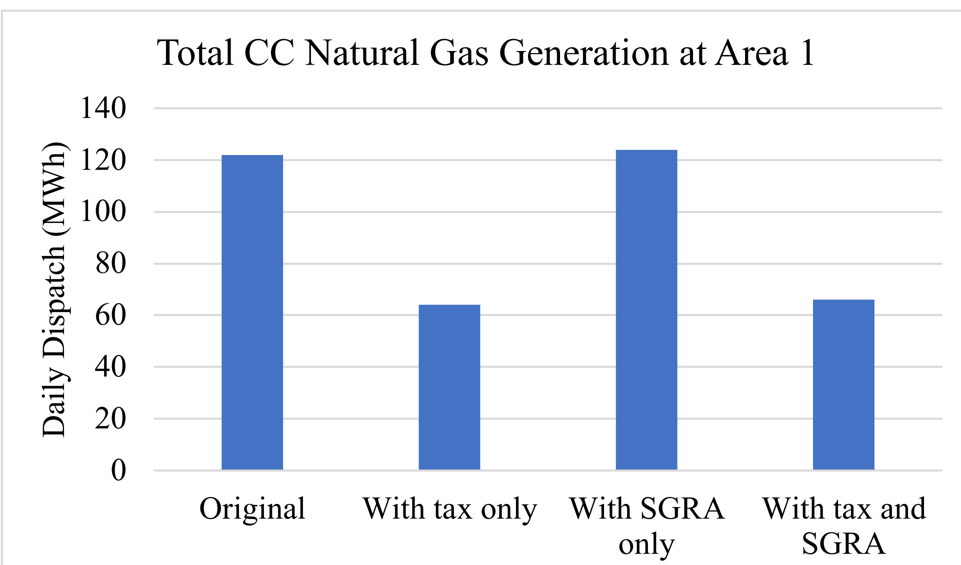

Figure 4-24: Comparison of CC natural gas generation dispatches in area 1 using different methods

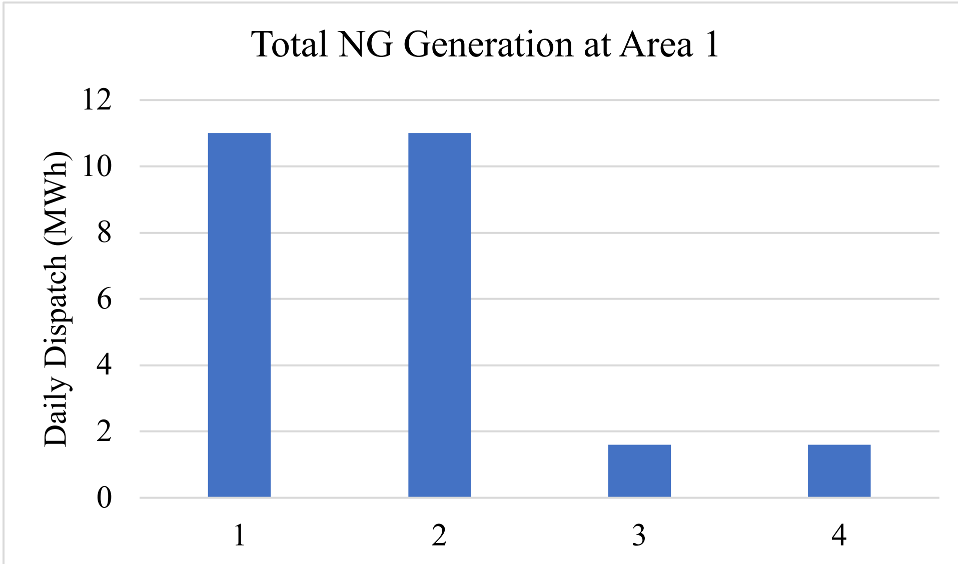

Figure 4-25: Comparison of natural gas generation dispatches in area 1 using different methods

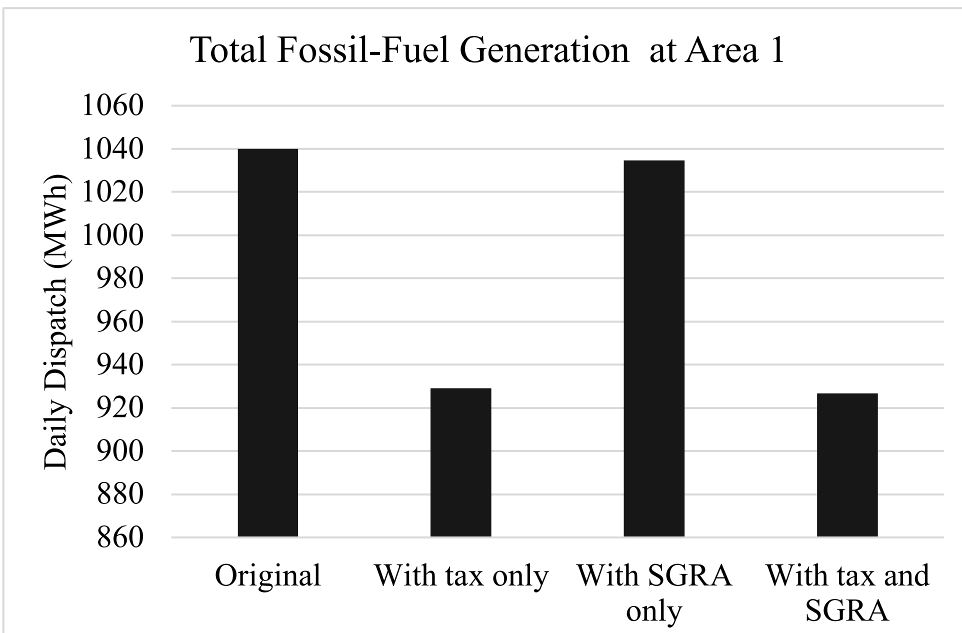

Figure 4-26: Comparison of fossil fuel generation dispatches in area 1 using different methods

Figure 4-27, Figure 4-28, Figure 4-29, and Figure 4-30 show the daily dispatches using the aforementioned different methods of C generators, CC generators, NG generators, and all fossil-fuel generators in area 2, respectively. Figure 4-31 shows the daily CO_2 emissions produced by fossil-fuel generators in area 1 and 2 for each method.

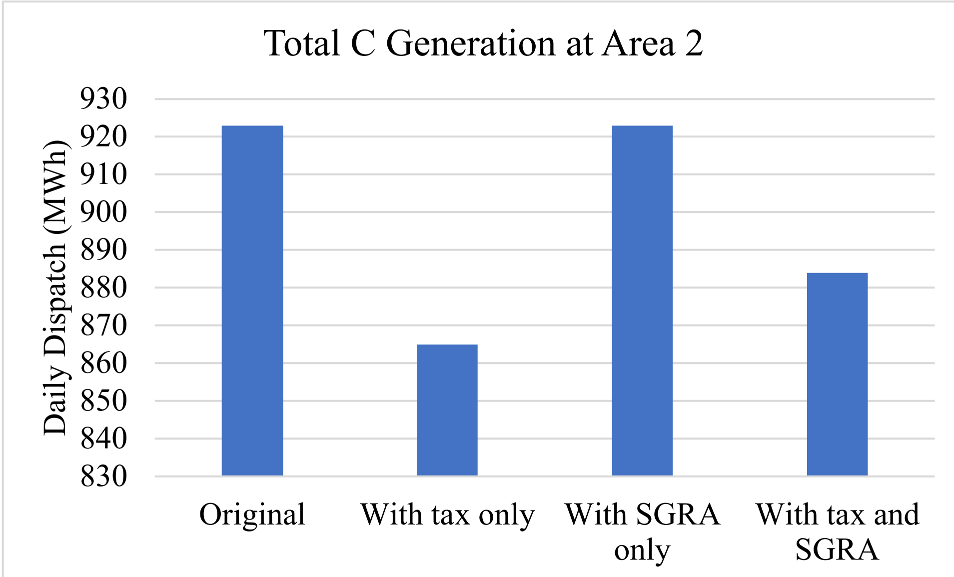

Figure 4-27: Comparison of coal generation dispatches in area 2 using different methods

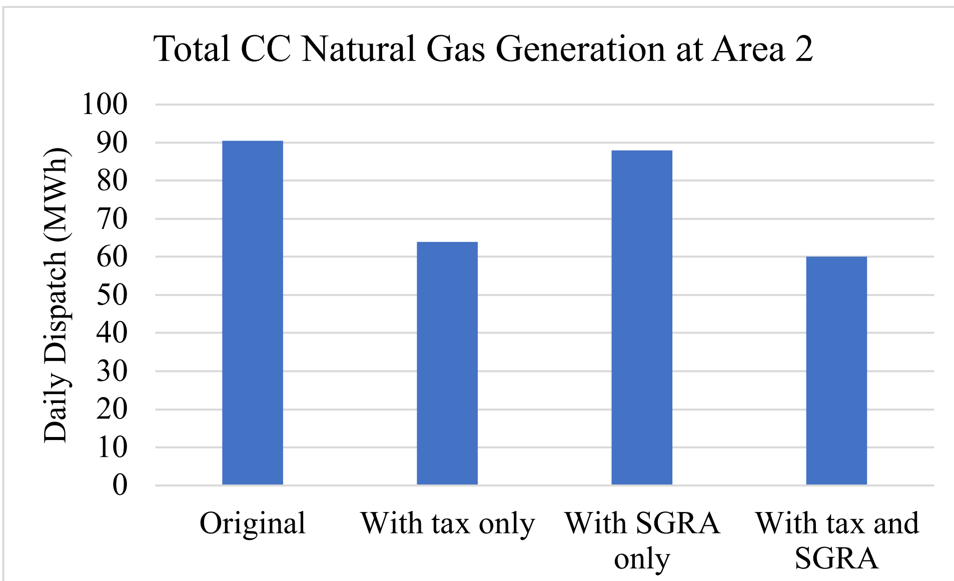

Figure 4-28: Comparison of CC natural gas generation dispatches in area 2 using different methods

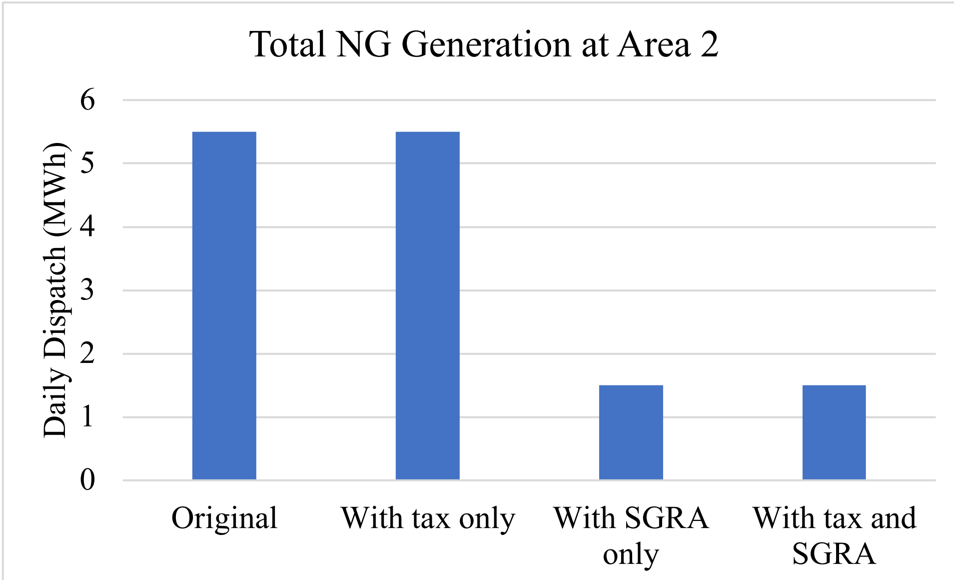

Figure 4-29: Comparison of natural gas generation dispatches in area 2 using different methods

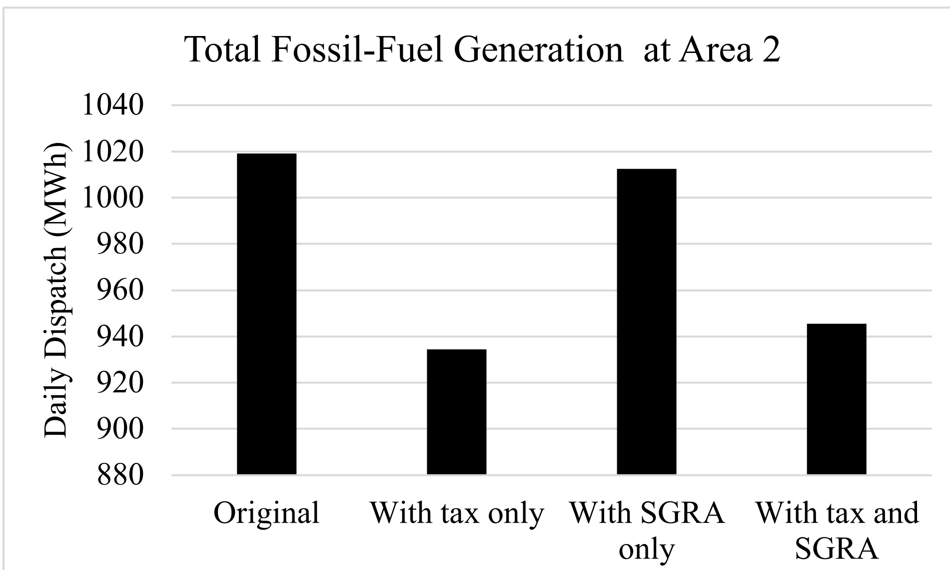

Figure 4-30: Comparison of fossil fuel generation dispatches in area 2 using different methods

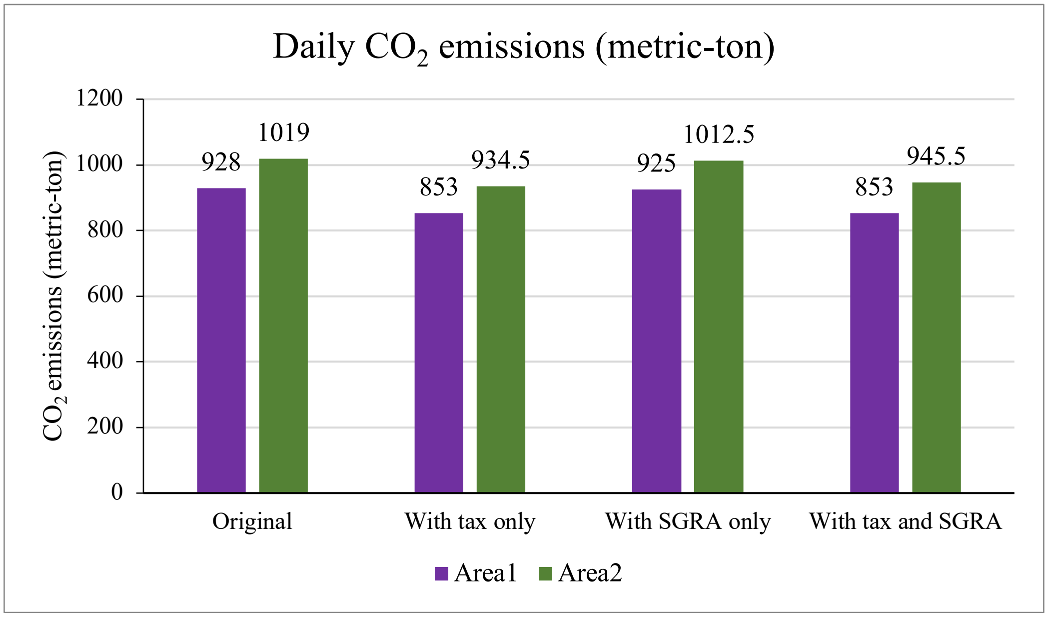

Figure 4-31: Comparison of daily CO_2 emissions in area 1 and 2 using different methods

4.5 Conclusion and Future Work

Carbon taxation for fossil-fuel based generation has promising potential not only to reduce GHG emissions but also to support the emergence of other types of generation. We introduce a carbon tax function for fossil-fueled generators based on emission rates for electricity production. Carbon taxation should grow annual to further suppress or mitigate the imminent danger of climate change as its effects are anticipated to worsen in the future. We show that carbon taxation raises electricity prices but, that will bring potential advantages to the grid in the long term.

The SGRA approach has potential to offer many benefits to the entire power grid. It allows an aggregator to provide peak demand reductions to electricity markets by performing a load shifting technique. It offers a day-ahead schedule and incentive pricing to residential assets in such a way that maximize its profits. Not only does it provide advantages at distribution network level, but it also influences the performance of power grid at generation and transmission levels. In this chapter, we show the benefits of the SGRA approach at a fully defined power system simulated using the RBTS system. We show how a number of SGRA-based aggregators at different load locations and areas in the network can be integrated into a DRX market in a day-ahead time frame. The integration of aggregators can supersede the utilization of peaking units in providing peaking services. This reduces electricity prices at peak times and cut down on the GHG emissions of peaking units.

The levied carbon tax on coal and natural gas generators has affected their dispatch under OPF because these generators have become more high-priced and less competitive than other types of power plants. We quantified how much emissions reductions achieved by the applied carbon taxation. However, the carbon taxation is designed to increase 5% annually, which is expected to further affect fossil-fueled generators. The effect of the increasing taxation is to be studied in future work.

The SGRA approach for DR when combined with carbon taxation shows economic and environmental benefits in reducing the CFs of both the peaking and non-peaking fossil fuel-based units. The main benefit of the SGRA approach is the significant reduction in the output of peaking units; however, this reduction in peak energy use is deferred to other off-peak times when fossil-fueled base load units may continue to pollute. Applying carbon taxes on all fossil-fueled generators achieves reductions in their dispatches, thus realizing holistic reductions in CO_2 emissions. The downside of solely applying the carbon taxes is considerably affecting electricity prices; but, that impact on electricity prices is alleviated when the carbon taxes are combined with the SGRA approach as indicated by the MEP from the simulations.

Carbon capture and sequestration (CCS) technologies will be more appealing to fossil-fueled generators to reduce their emission rates and, consequently decrease their tax expenditures. The revenue received from carbon taxation can be recycled in different ways such as investing in renewable energy generation technologies or reducing tax rates of other sectors of the economy. The tax revenue recycling needs further investigation and is left for future work.

CHAPTER 5

ASSESSMENT OF AGGREGATORS PERFORMANCE WITH DIFFERENT PRICING SYSTEMS

5.1 Overview

In this chapter, we evaluate how the SGRA-based aggregators behave in our test system (RBTS) with different types of pricing systems. The purpose of this evaluation experiment in this chapter is to find the pricing system with which the aggregator makes the most profits and the maximum load shift at peak time.

5.2 Introduction

There are different types of electricity pricing system. The general classifications are time-independent pricing rates and time-varying pricing rates [76]. The first category includes flat rates and tiered rates. The flat rates are fixed tariff during a specific period of time (e.g., 30-day billing cycle) and they are completely independent of time and quantity of consumption during this period. As for the tiered rates, these rates charge different prices based on tiers of usage. Customers will be charged a higher price for a higher consumption. This type of pricing is designed to encourage less energy consumptions for a number of benefits technically and environmentally.

The other category is time dependent that is designed to send signals to customers in order to encourage them change their energy consumption behavior as responses to these signals, which what we call DR as we elaborately explained in chapter 2 [77]. This category includes real-time and TOU pricing systems and others.

In this chapter, we use three different electricity pricing systems for the utilities at each load bus to evaluate the outputs of aggregators 2-6 in our system. For the first case, we assign flat rates for the utilities at all load buses in the system. For the second case, we select real-time pricing rates for the utilities at all load buses in the system. For the last case, we apply TOU pricing rates for the utilities in the system

5.3 Fixed Tariffs

In this case study where we assume that the utilities at the areas of the aggregators in the system apply flat rates. We use 5 different flat rates taken from 5 different areas in the network of PJM [78], [79], [80], [81], [82]. We insert theses flat rates as retail prices applied by the utilities and perform the SGRA technique to find the outputs of the aggregators starting from aggregator 2 to aggregator 6

Aggregator 2

Figure 5-1 shows the spot market prices, the utility prices, and the CIP performed by the aggregator at bus 2.

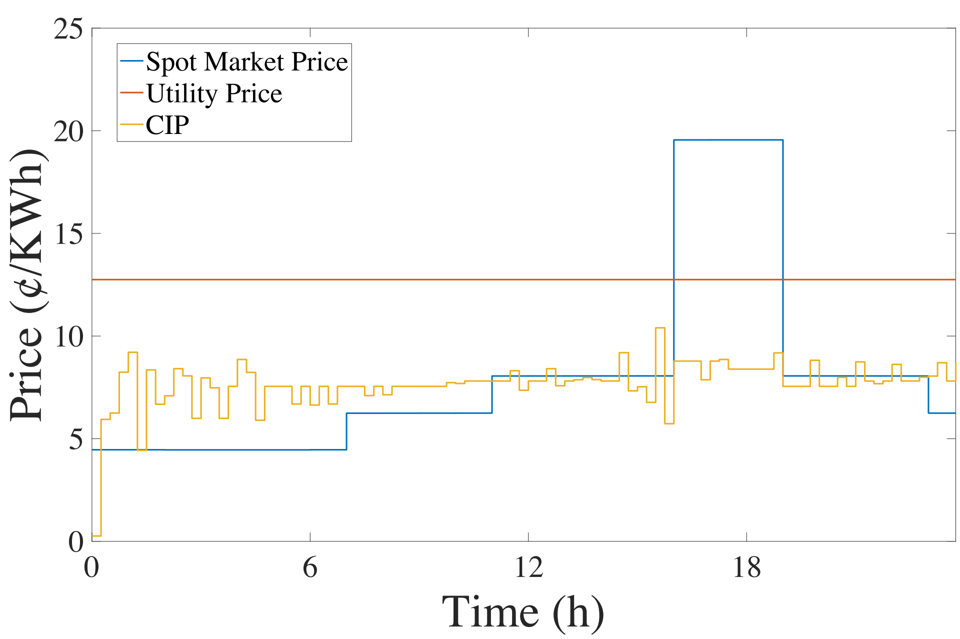

Figure 5-1: Spot market price, utility fixed tariff, and CIP of aggregator 2

The profiles of the schedulable loads in the distribution system of bus 2 are shown in Figure 5-2. The load before rescheduling is labeled as original and the load after rescheduling is labeled as rescheduled and they both are demonstrated in the following graph.

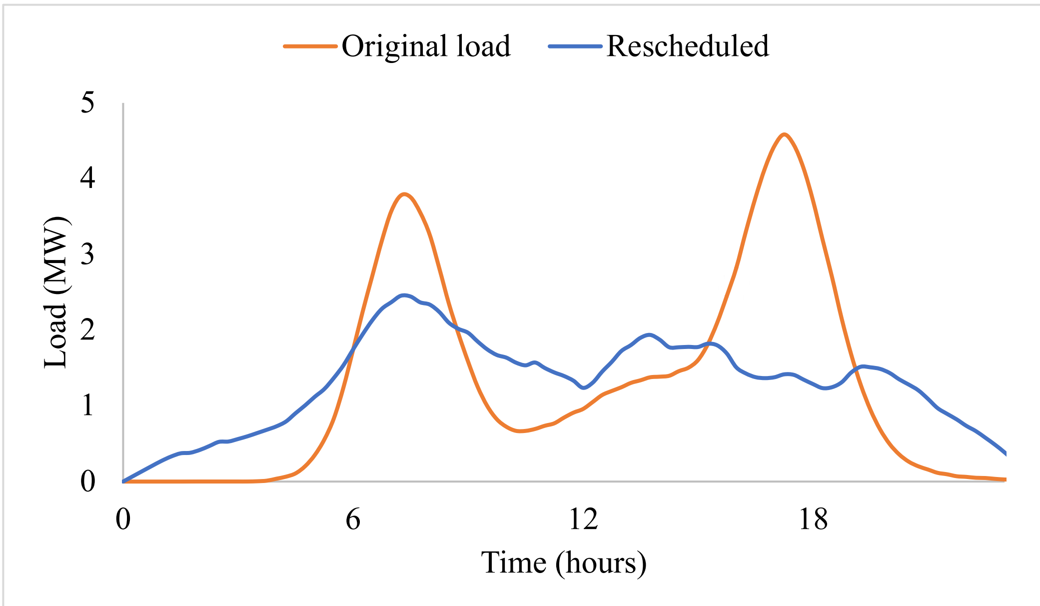

Figure 5-2: Original and rescheduled controllable load of aggregator 2 with fixed tariff

Aggregator 3

Figure 5-3 shows the spot market prices, the utility prices, and the CIP performed by the aggregator at bus 3.

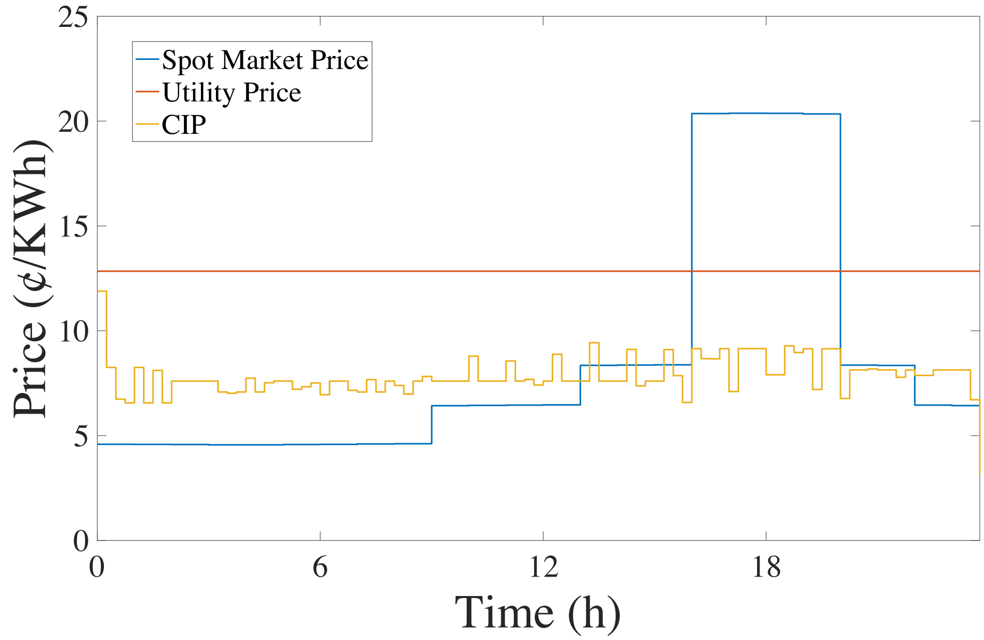

Figure 5-3: Spot market price, utility fixed tariff, and CIP of aggregator 3

The profiles of the schedulable loads in the distribution system of bus 3 are shown in the following graph. The load before rescheduling is labeled as original and the load after rescheduling is labeled as rescheduled and they both are demonstrated in Figure 5-4.

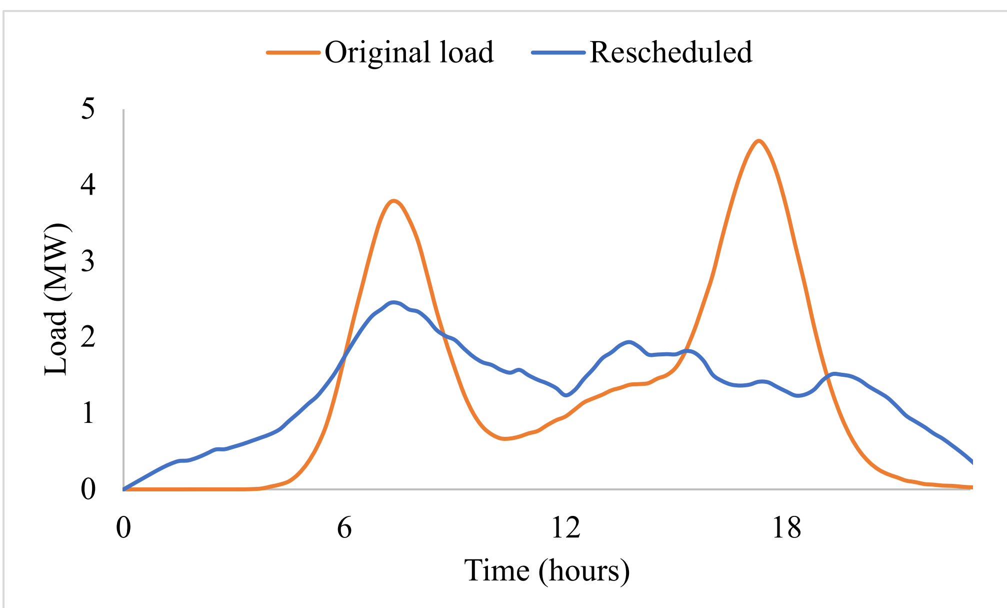

Figure 5-4: Original and rescheduled controllable load of aggregator 3 with fixed tariff

Aggregator 4

Figure 5-5 shows the spot market prices, the utility prices, and the CIP performed by the aggregator at bus 4.

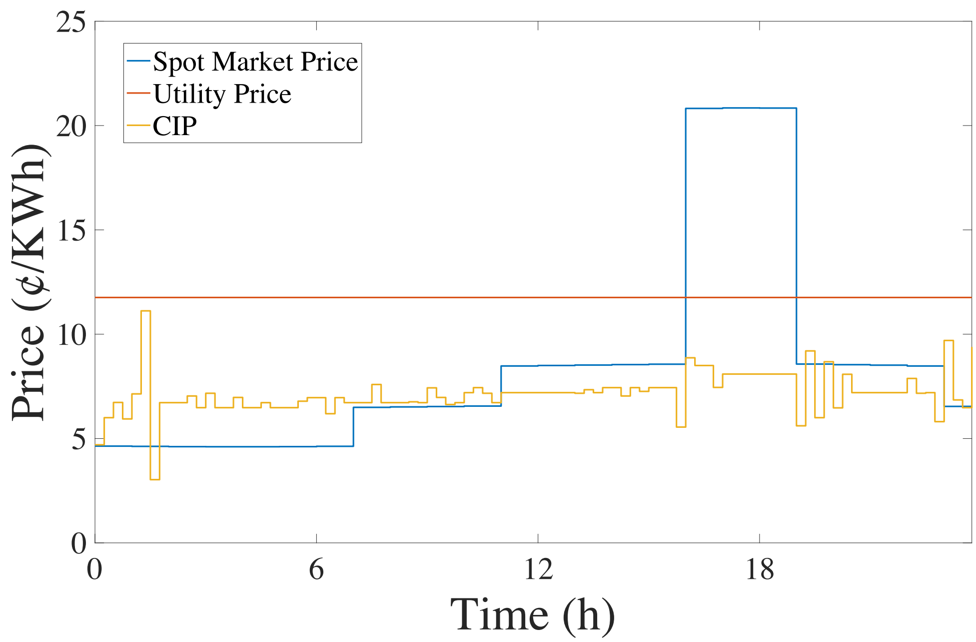

Figure 5-5: Spot market price, utility fixed tariff, and CIP of aggregator 4

The profiles of the schedulable loads in the distribution system of bus 4 are shown in the following graph. The load before rescheduling is labeled as original and the load after rescheduling is labeled as rescheduled and they both are demonstrated in Figure 5-6.

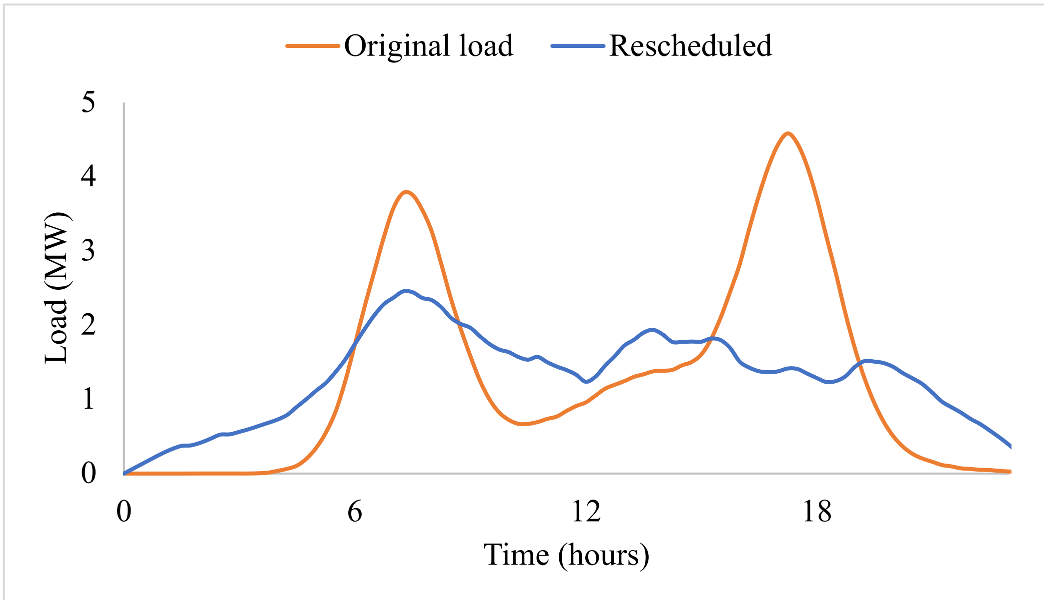

Figure 5-6: Original and rescheduled controllable load of aggregator 4 with fixed tariff

Aggregator 5

Figure 5-7 shows the spot market prices, the utility prices, and the CIP performed by the aggregator at bus 5.

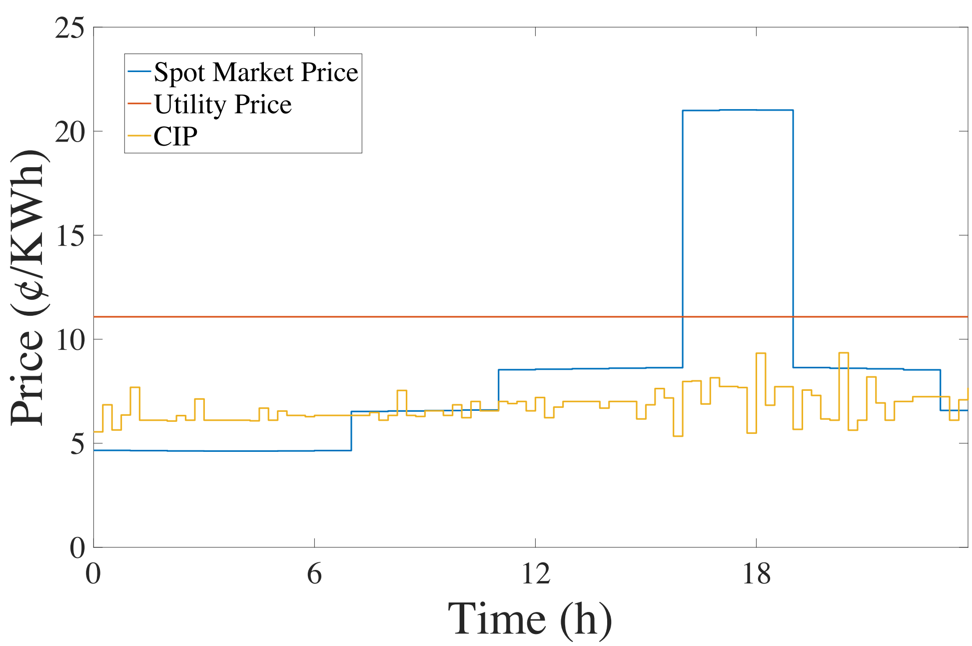

Figure 5-7: Spot market price, utility fixed tariff, and CIP of aggregator 5

The profiles of the schedulable loads in the distribution system of bus 5 are shown in the following graph. The load before rescheduling is labeled as original and the load after rescheduling is labeled as rescheduled and they both are demonstrated in Figure 5-8.

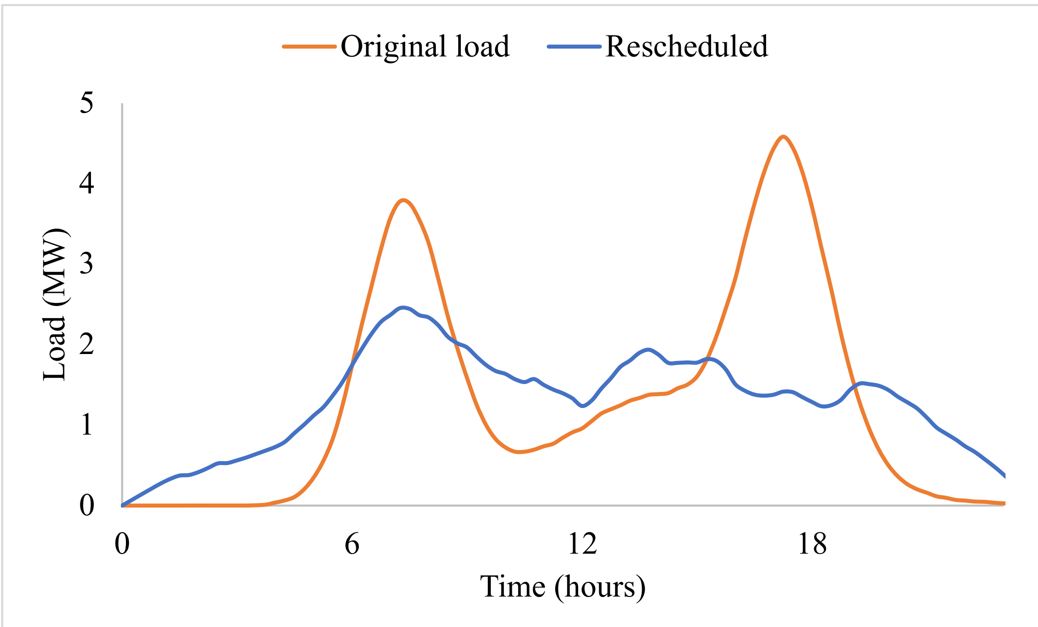

Figure 5-8: Original and rescheduled controllable load of aggregator 5 with fixed tariff

Aggregator 6

Figure 5-9 shows the spot market prices, the utility prices, and the CIP performed by the aggregator at bus 6.

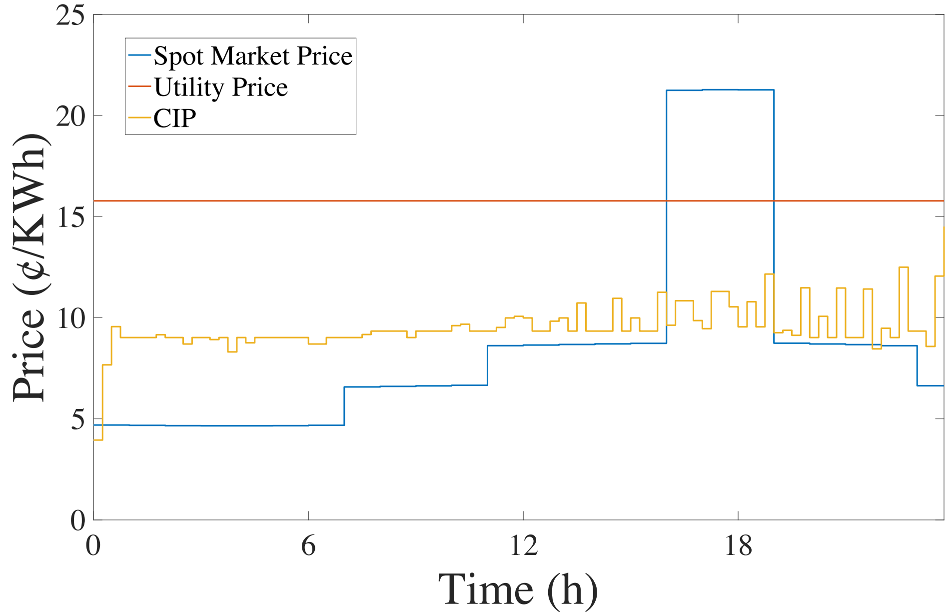

Figure 5-9: Spot market price, utility fixed tariff, and CIP of aggregator 6

The profiles of the schedulable loads in the distribution system of bus 6 are shown in the following graph. The load before rescheduling is labeled as original and the load after rescheduling is labeled as rescheduled and they both are demonstrated in Figure 5-10.

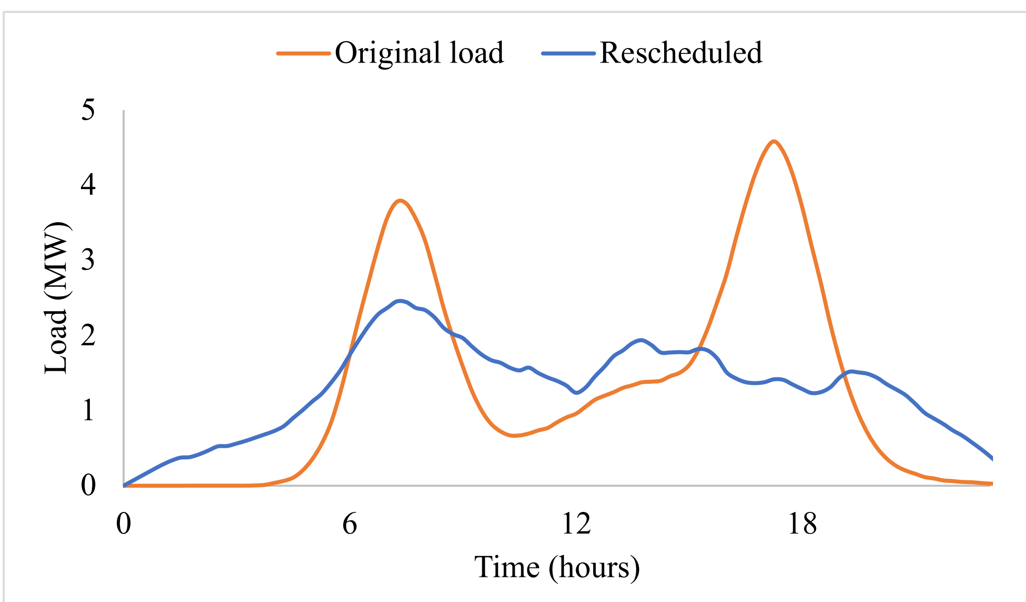

Figure 5-10: Original and rescheduled controllable load of aggregator 6 with fixed tariff

The profits of each aggregators with different fixed tariffs are shown in Table 5-1, which also shows the maximum load shifted from peak times.

Table 5-1: Profits and peak load shifted of aggregators with varying utilities fixed tariffs

Aggregators #	Profit ($)	Utility's Fixed Tariff (¢/KWh))	Shifted Peak Load (MWh)
2	2978.14	12.75	25.02
3	2987.49	12.84	25.6
4	2862.59	11.76	25.35
5	2747.36	11.08	25.01
6	3572.62	15.78	24.37
Average	**3029.64**	**12.84**	**25.07**

5.4 RT Pricing

In this case study where we assume that the utilities at the areas of the aggregators in the system apply RT pricing rates. The RT pricing should reflect the energy prices in the wholesale market in addition to 10% for other charges such as delivery charges and taxes. We insert theses RT pricing rates as retail prices applied by the utilities and perform the SGRA technique to find the outputs of the aggregators starting from aggregator 2 to aggregator 6.

Aggregator 2

Figure 5-11 shows the spot market prices, the utility prices, and the CIP performed by the aggregator at bus 2.

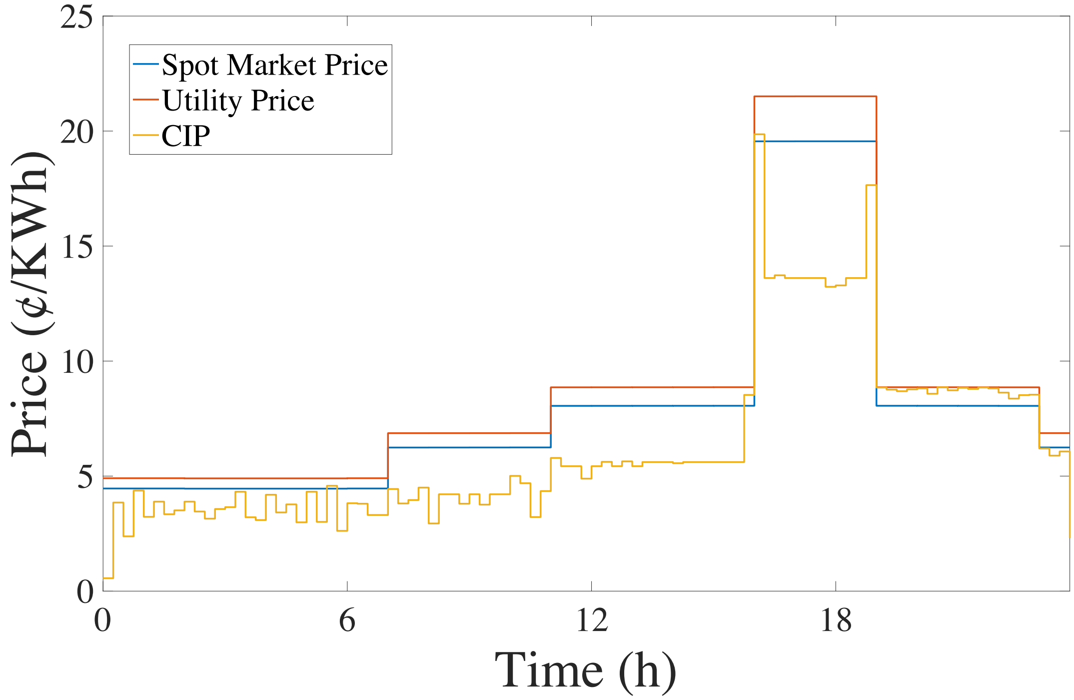

Figure 5-11: Spot market price, utility RTP, and CIP of aggregator 2

The profiles of the schedulable loads in the distribution system of bus 2 are shown in the following graph. The load before rescheduling is labeled as original and the load after rescheduling is labeled as rescheduled and they both are demonstrated in Figure 5-12.

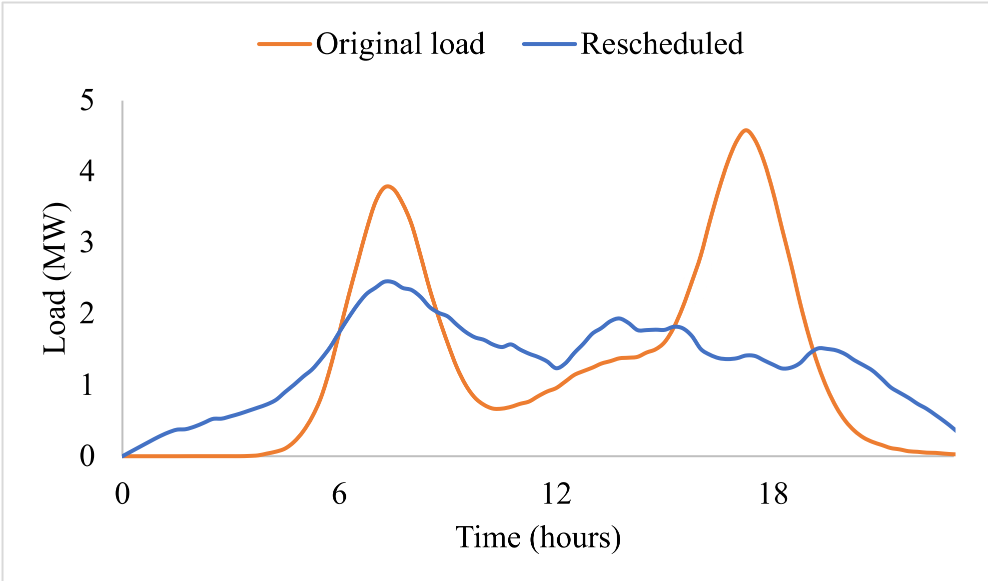

Figure 5-12: Original and rescheduled controllable load of aggregator 2 with RTP

Aggregator 3

Figure 5-13 shows the spot market prices, the utility prices, and the CIP performed by the aggregator at bus 3.

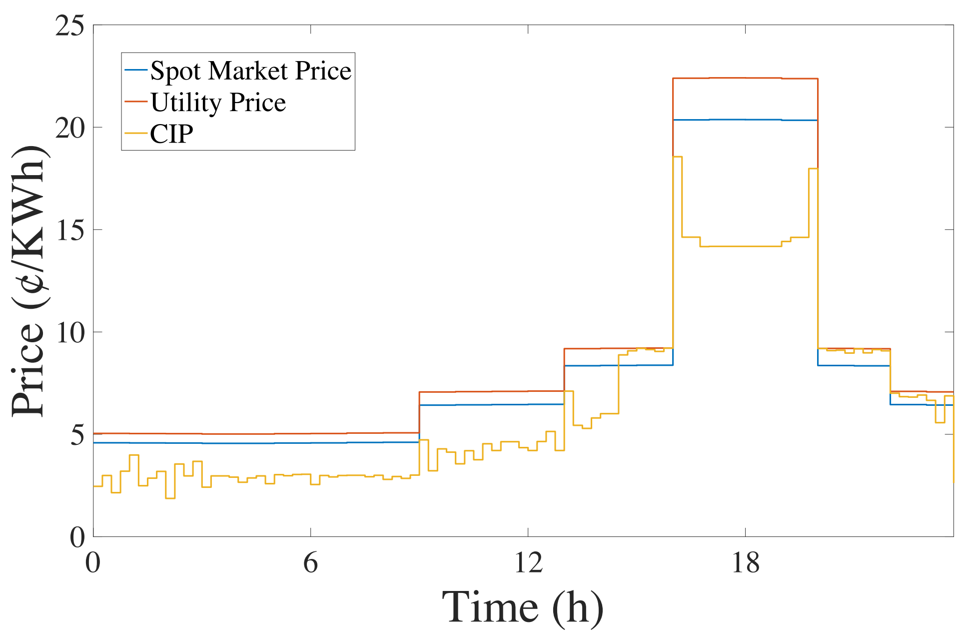

Figure 5-13: Spot market price, utility RTP, and CIP of aggregator 3

The profiles of the schedulable loads in the distribution system of bus 3 are shown in the following graph. The load before rescheduling is labeled as original and the load after rescheduling is labeled as rescheduled and they both are demonstrated in Figure 5-14.

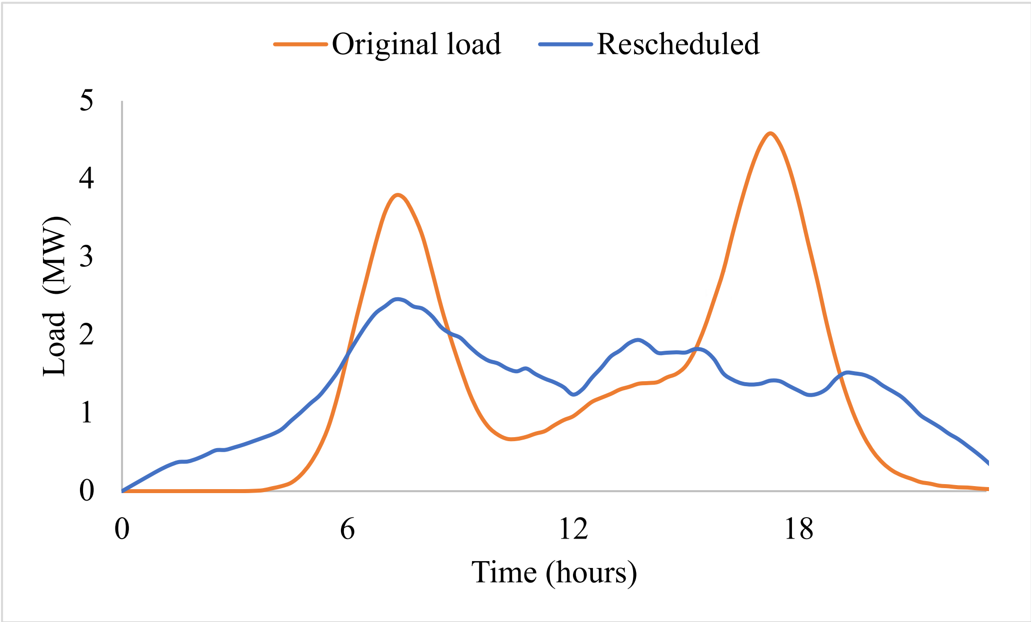

Figure 5-14: Original and rescheduled controllable load of aggregator 3 with RTP

Aggregator 4

Figure 5-15 shows the spot market prices, the utility prices, and the CIP performed by the aggregator at bus 4.

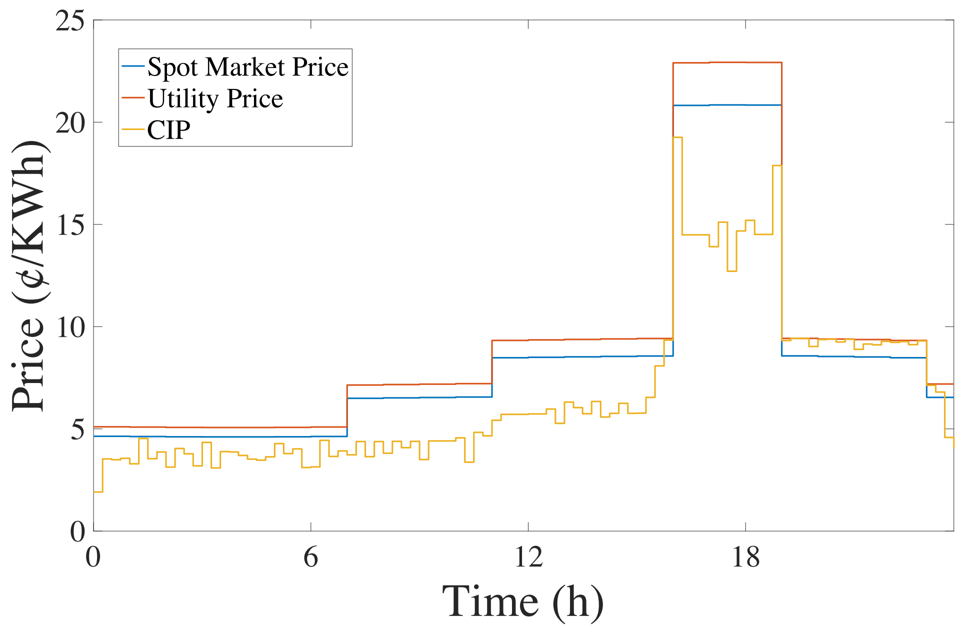

Figure 5-15: Spot market price, utility RTP, and CIP of aggregator 4

The profiles of the schedulable loads in the distribution system of bus 4 are shown in the following graph. The load before rescheduling is labeled as original and the load after rescheduling is labeled as rescheduled and they both are demonstrated in Figure 5-16.

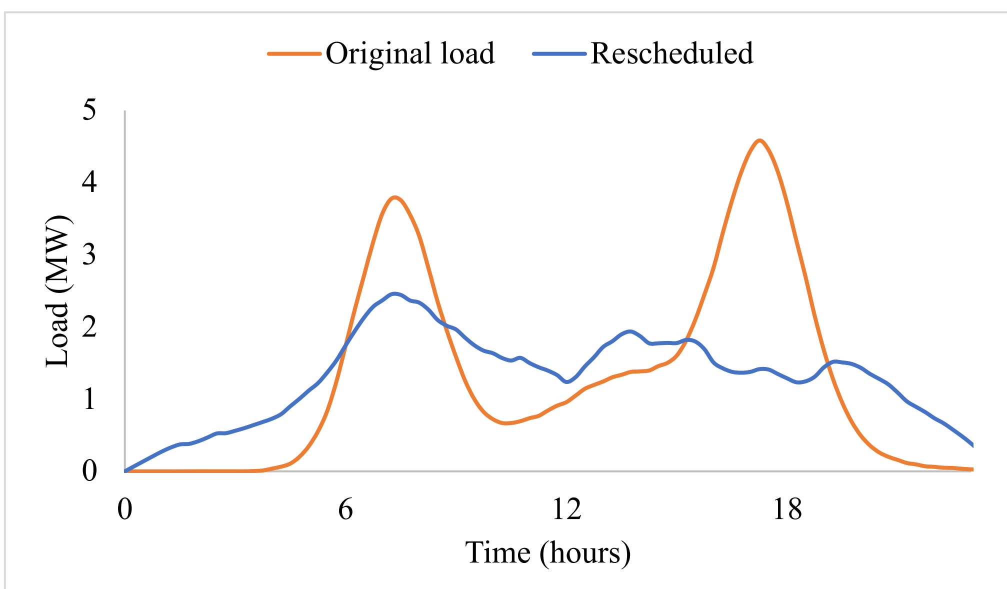

Figure 5-16: Original and rescheduled controllable load of aggregator 4 with RTP

Aggregator 5

Figure 5-17 shows the spot market prices, the utility prices, and the CIP performed by the aggregator at bus 5.

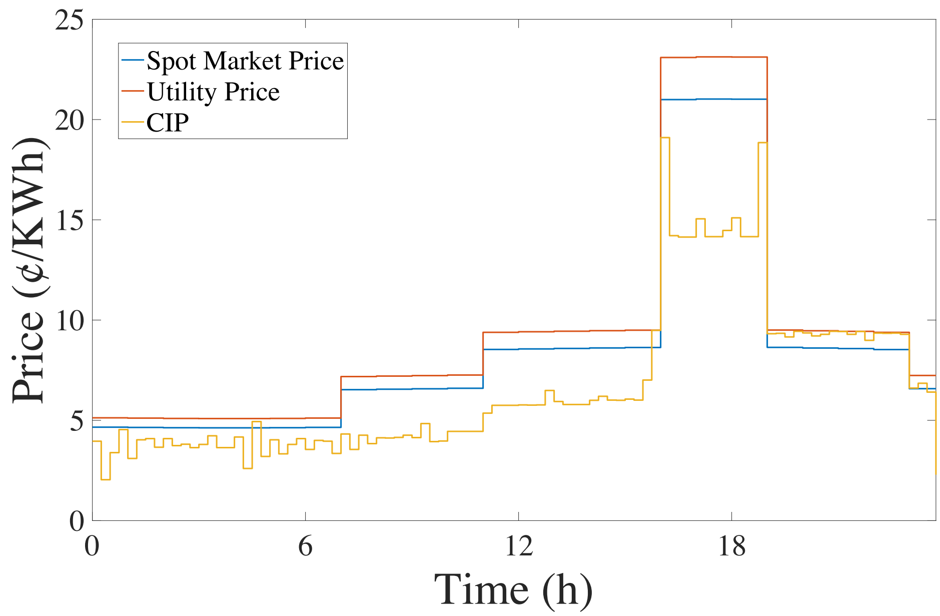

Figure 5-17: Spot market price, utility RTP, and CIP of aggregator 5

The profiles of the schedulable loads in the distribution system of bus 5 are shown in the following graph. The load before rescheduling is labeled as original and the load after rescheduling is labeled as rescheduled and they both are demonstrated in Figure 5-18.

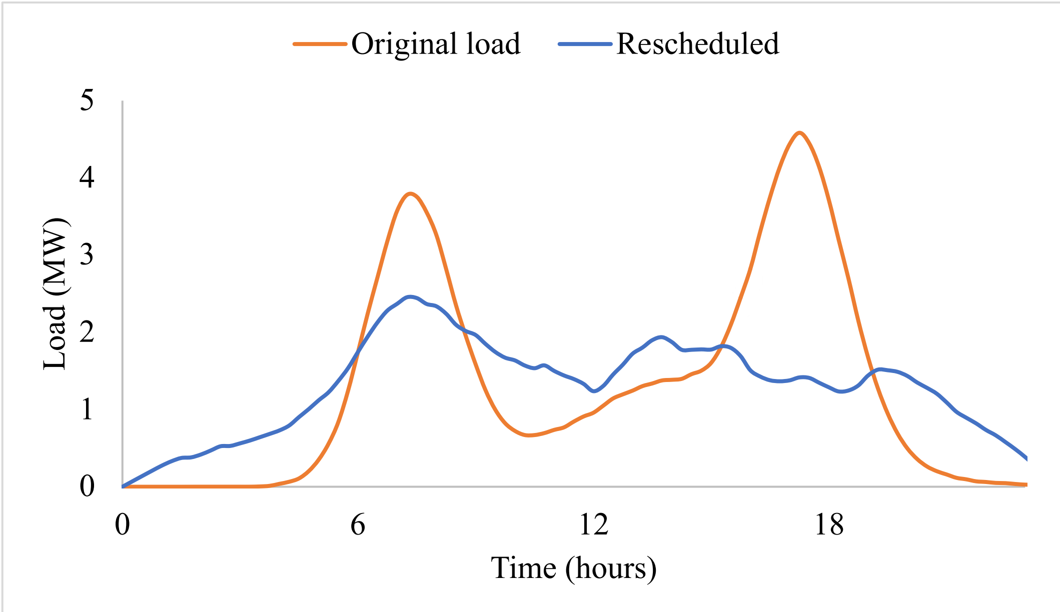

Figure 5-18: Original and rescheduled controllable load of aggregator 5 with RTP

Aggregator 6

Figure 5-19 shows the spot market prices, the utility prices, and the CIP performed by the aggregator at bus 6.

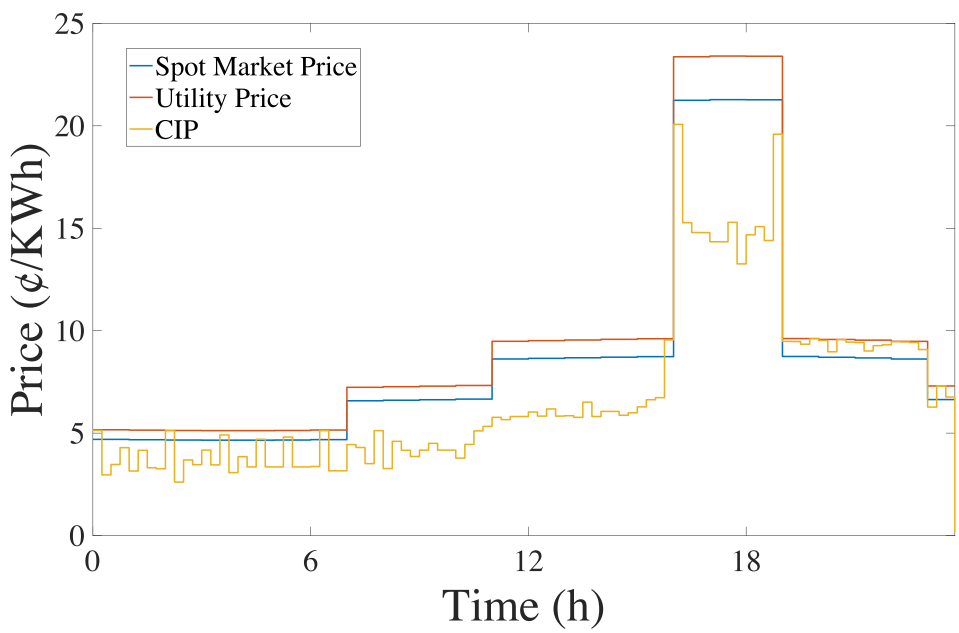

Figure 5-19: Spot market price, utility RTP, and CIP of aggregator 6

The profiles of the schedulable loads in the distribution system of bus 6 are shown in the following graph. The load before rescheduling is labeled as original and the load after rescheduling is labeled as rescheduled and they both are demonstrated in Figure 5-20.

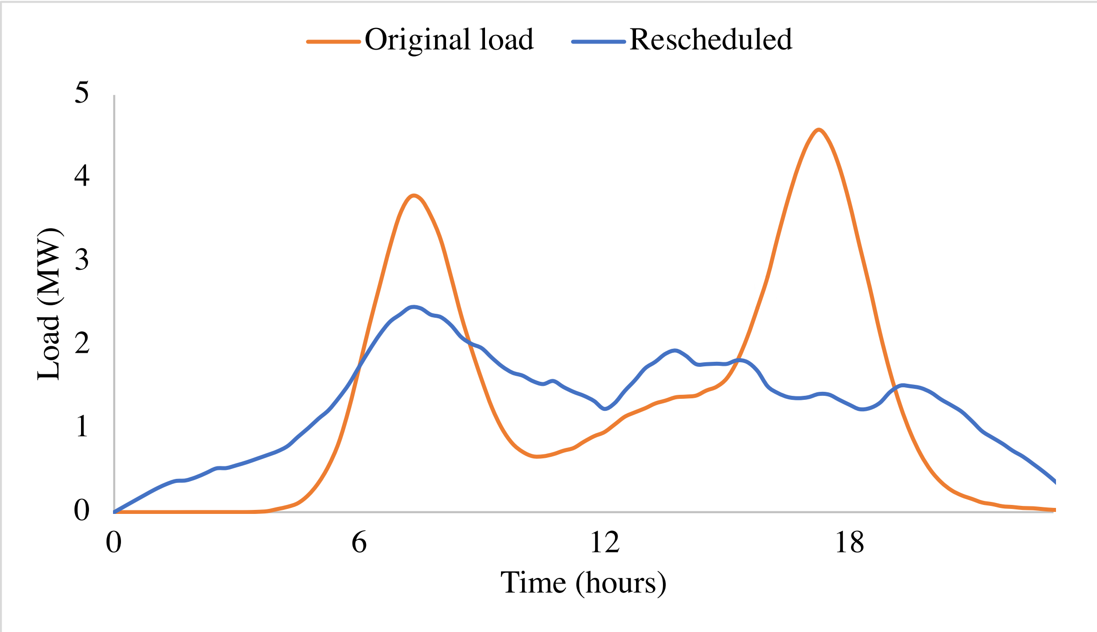

Figure 5-20: Original and rescheduled controllable load of aggregator 6 with RTP

The profits of each aggregators with different RTP rates are shown in the Table 5-2, which also shows the maximum load shifted from peak times.

Table 5-2: Profits and peak load shifted of aggregators with varying utilities RT pricings

Aggregators #	Profit ($)	Shifted Peak Load (MWh)
2	2425.23	26.77
3	2530.01	28.91
4	2588.80	27.24
5	2611.24	27.13
6	2631.32	27.17
Average	**2557.32**	**27.44**

5.5 TOU Pricing

In this case study where we assume that the utilities at the areas of the aggregators in the system apply TOU pricing rates. It is designed such that the electricity prices are high at peak times and low at off-peak times. We use data of TOU pricing from The Potomac Electric Power Company (PEPCO) [83]. We insert theses TOU pricing rates as retail prices applied by the utilities and perform the SGRA technique to find the outputs of the aggregators 2–6.

Aggregator 2

Figure 5-21 shows the spot market prices, the utility prices, and the CIP performed by the aggregator at bus 2.

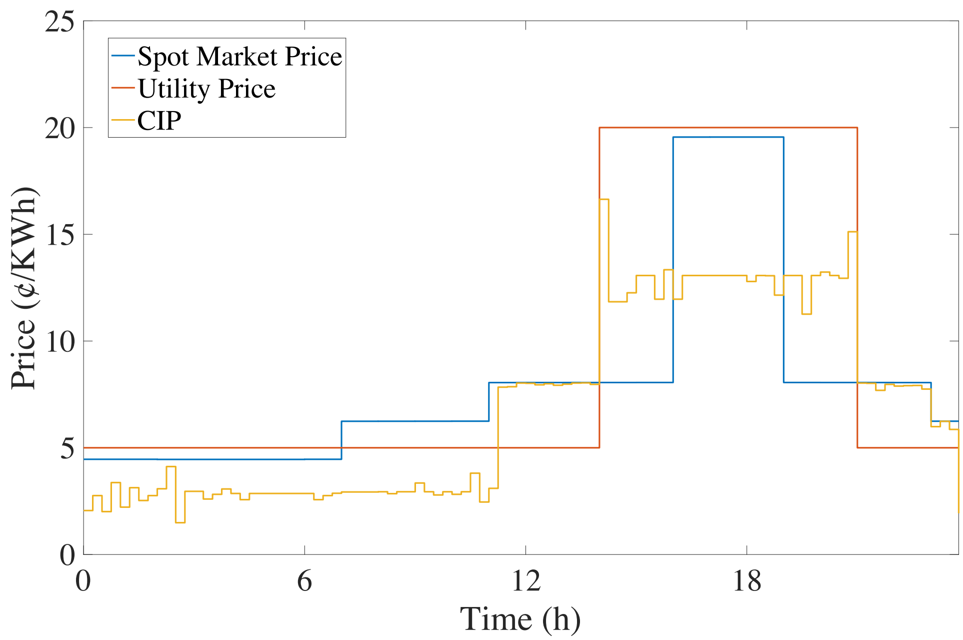

Figure 5-21: Spot market price, utility TOU pricing, and CIP of aggregator 2

The profiles of the schedulable loads in the distribution system of bus 2 are shown in the following graph. The load before rescheduling is labeled as original and the load after rescheduling is labeled as rescheduled and they both are demonstrated in Figure 5-22.

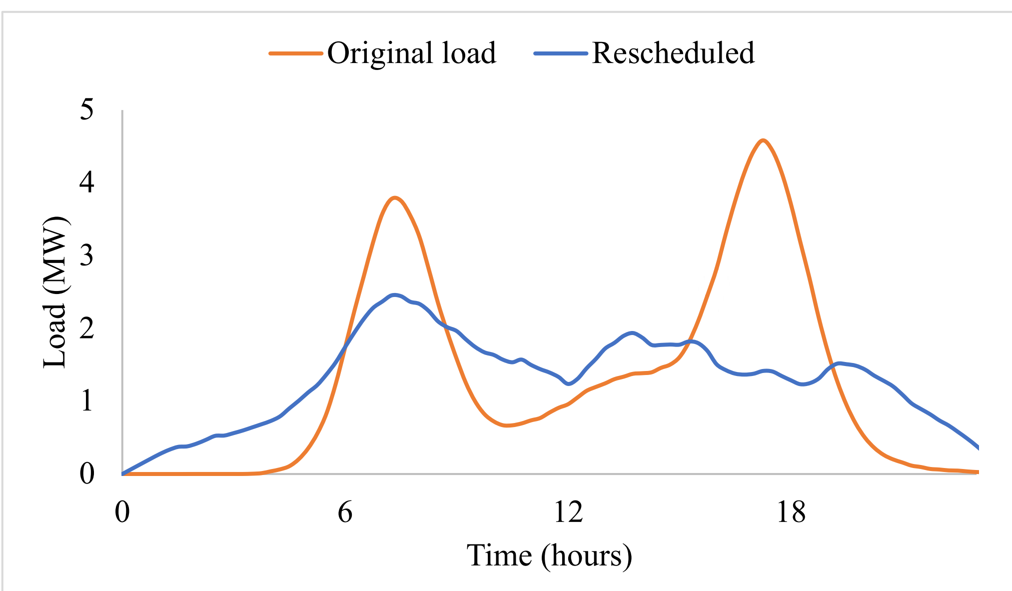

Figure 5-22: Original and rescheduled controllable load of aggregator 2 with TOU pricing

Aggregator 3

Figure 5-23 shows the spot market prices, the utility prices, and the CIP performed by the aggregator at bus 3.

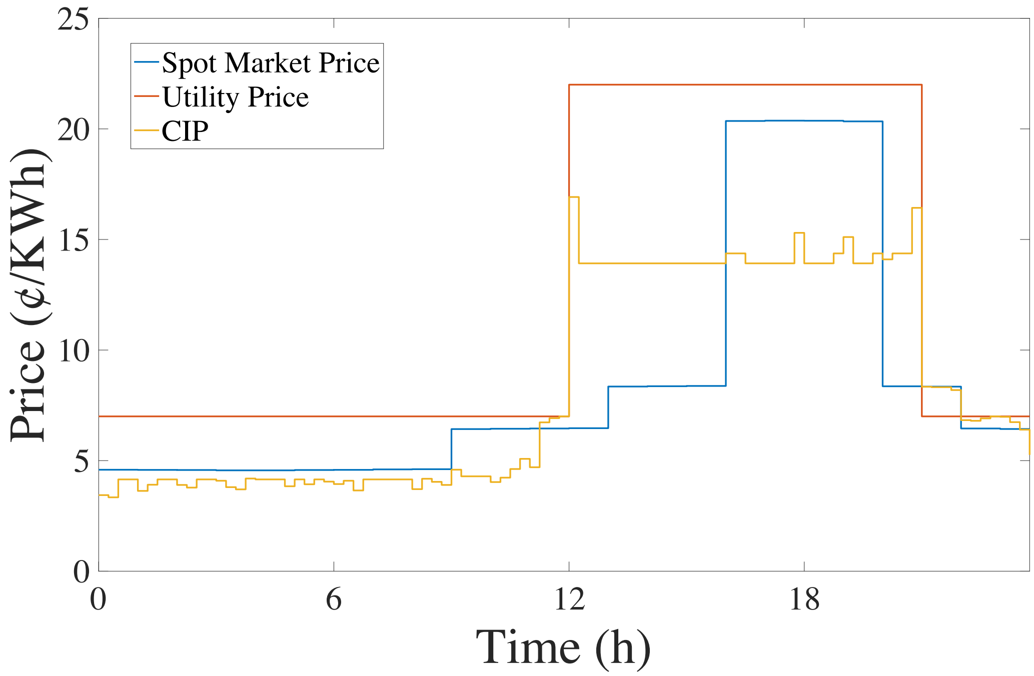

Figure 5-23: Spot market price, utility TOU pricing, and CIP of aggregator 3

The profiles of the schedulable loads in the distribution system of bus 3 are shown in the following graph. The load before rescheduling is labeled as original and the load after rescheduling is labeled as rescheduled and they both are demonstrated in Figure 5-24.

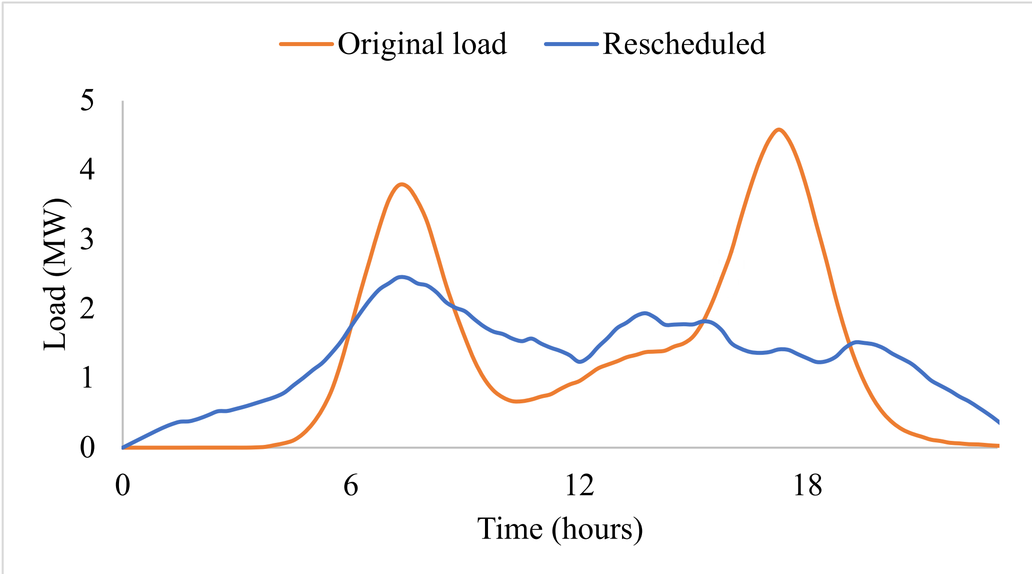

Figure 5-24: Original and rescheduled controllable load of aggregator 3 with TOU pricing

Aggregator 4

Figure 5-25 shows the spot market prices, the utility prices, and the CIP performed by the aggregator at bus 4.

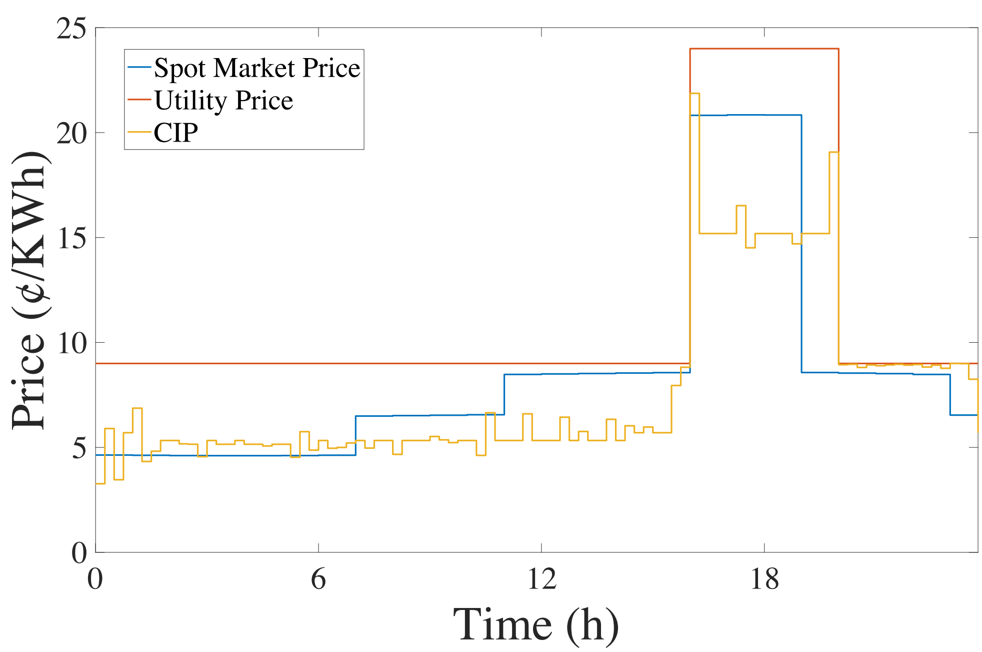

Figure 5-25: Spot market price, utility TOU pricing, and CIP of aggregator 4

The profiles of the schedulable loads in the distribution system of bus 4 are shown in the following graph. The load before rescheduling is labeled as original and the load after rescheduling is labeled as rescheduled and they both are demonstrated in Figure 5-26.

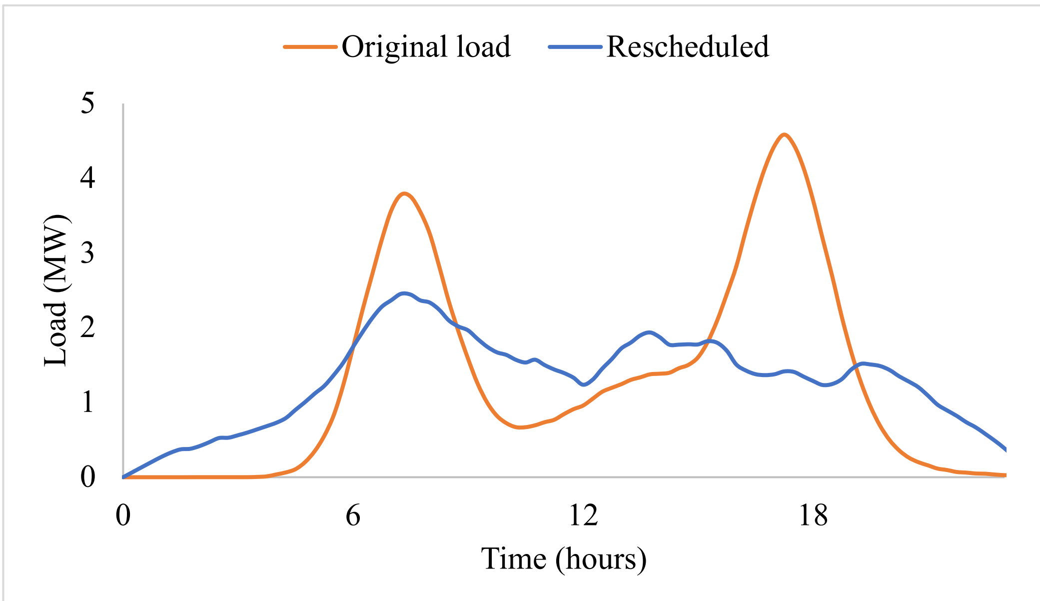

Figure 5-26: Original and rescheduled controllable load of aggregator 4 with TOU pricing

Aggregator 5

Figure 5-27 shows the spot market prices, the utility prices, and the CIP performed by the aggregator at bus 5.

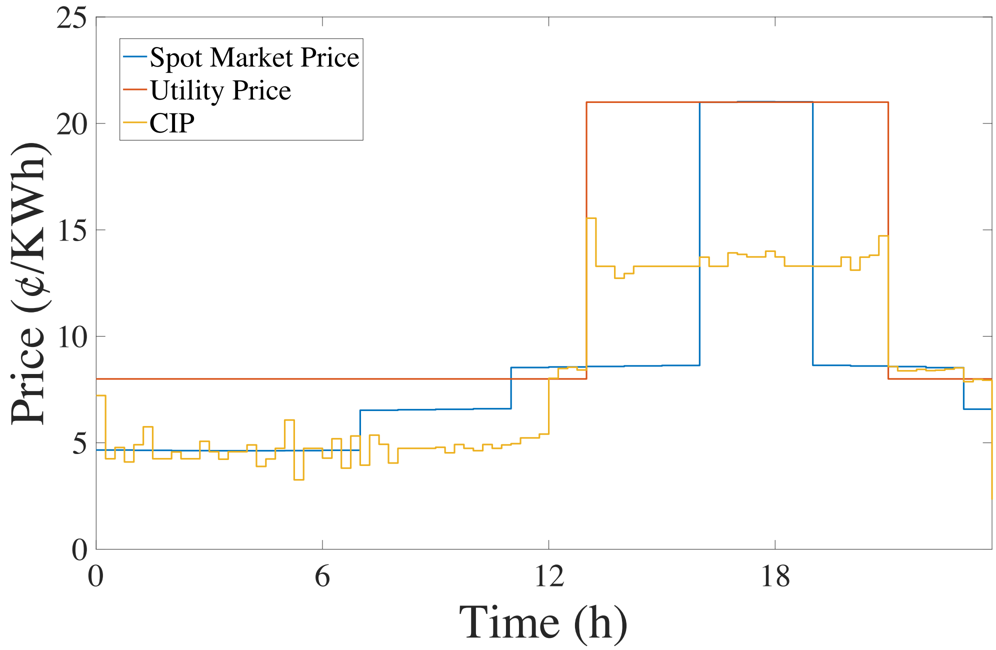

Figure 5-27: Spot market price, utility TOU pricing, and CIP of aggregator 5

The profiles of the schedulable loads in the distribution system of bus 5 are shown in the following graph. The load before rescheduling is labeled as original and the load after rescheduling is labeled as rescheduled and they both are demonstrated in Figure 5-28.

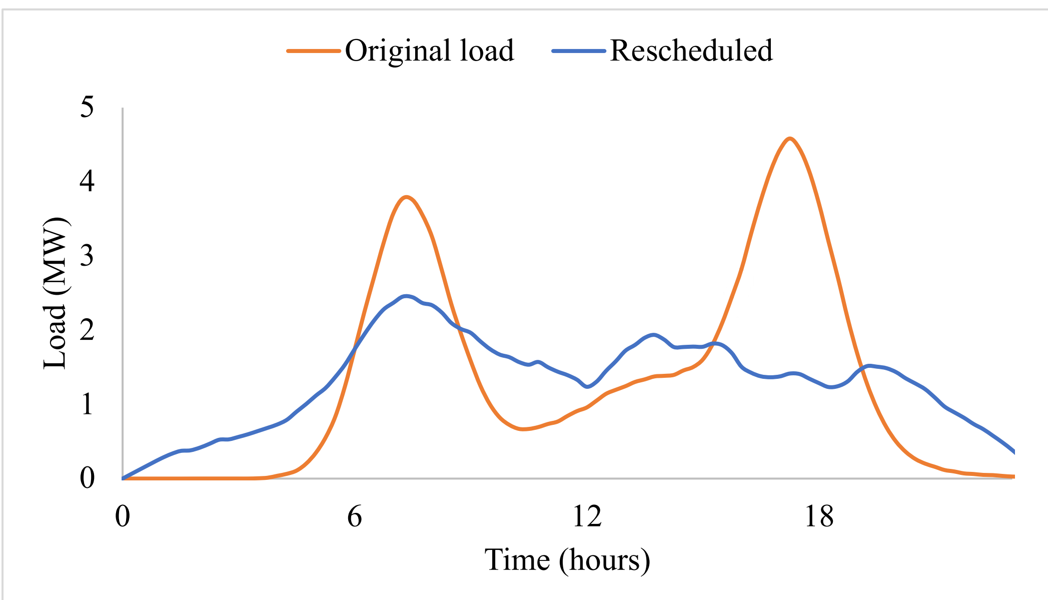

Figure 5-28: Original and rescheduled controllable load of aggregator 5 with TOU pricing

Aggregator 6

Figure 5-29 shows the spot market prices, the utility prices, and the CIP performed by the aggregator at bus 6.

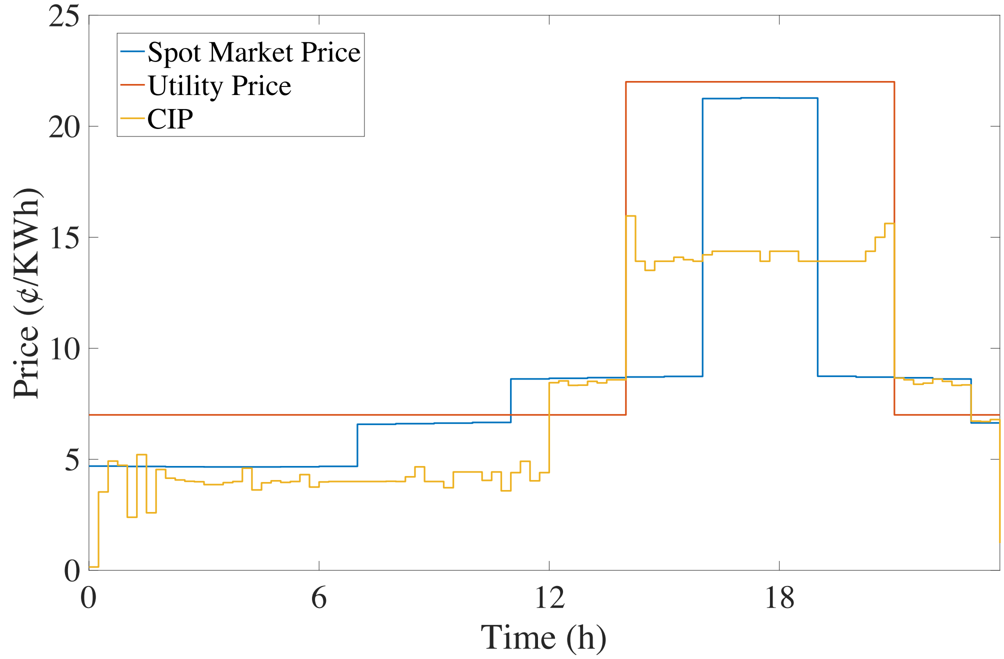

Figure 5-29: Spot market price, utility TOU pricing, and CIP of aggregator 6

The profiles of the schedulable loads in the distribution system of bus 6 are shown in the following graph. The load before rescheduling is labeled as original and the load after rescheduling is labeled as rescheduled and they both are demonstrated in Figure 5-30.

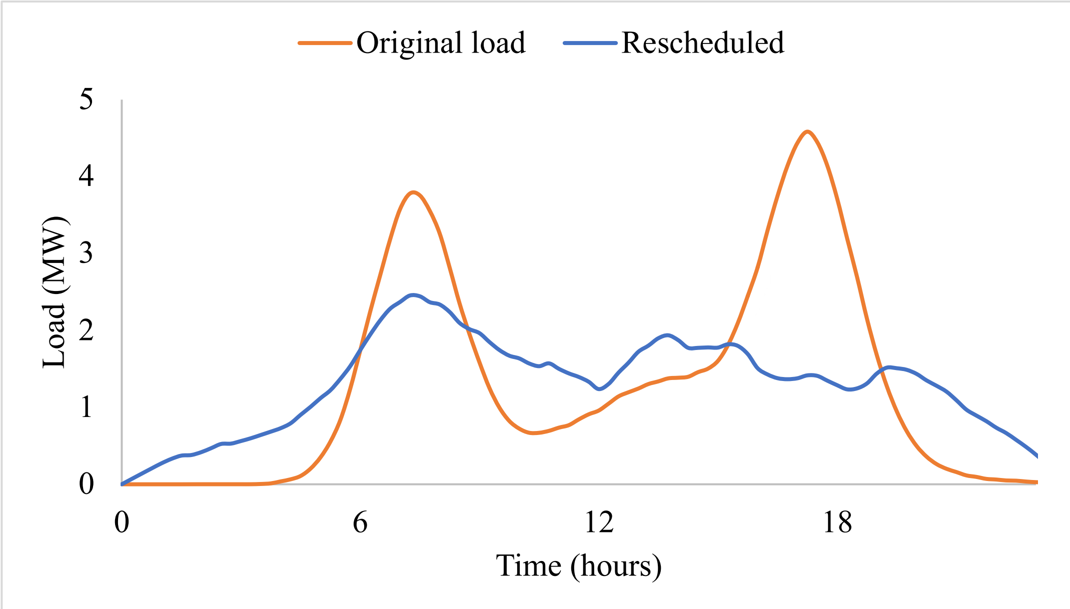

Figure 5-30: Original and rescheduled controllable load of aggregator 6 with TOU pricing

The profits of each aggregators with different fixed tariffs are shown Table 5-3, which also shows the maximum load shifted from peak times.

Table 5-3: Profits and peak load shifted of aggregators with varying utilities TOU pricings

Aggregators #	Profit ($)	Shifted Peak Load (MWh)
2	2702	25.48
3	3226.46	26.34
4	2922.51	26.46
5	3181.78	25.56
6	3050.44	25.70
Average	**3016.638**	**25.91**

5.6 Conclusion

In conclusion, the aggregators make the largest peak load reduction when integrated with utilities applying RTP at an average of 3.33 MW. However, they make the least profits in comparison to the types of pricing systems at an average of about $2557.

The aggregators which are integrated with utilities offering fixed rates makes the most profits at an average of around $3030, but they bring the least peak load reduction.

As for the aggregators with TOU pricing-based utilities, they make more profits than the aggregators with RTP pricing-based utilities, but less than the aggregators with fixed tariff pricing-based utilities. That is due to the low off-peak prices for TOU pricing that the aggregators have to offer even lower prices to incentivize customers for participation.

CHAPTER 6

INCORPORATION OF RESCHEDULING CONSTRAINTS INTO RESIDENTIAL DR AGGREGATOR USING SURVEY-BASED DATA

6.1 Overview

Survey-based data of three home appliances are included in a residential DR aggregation algorithm that performs resource re-allocation for peak demand reduction in a notional electric distribution system. In addition, new constraints are integrated into the resource allocation approach to alleviate the inconvenience of the participating customers due to rescheduling their home appliances. Our effort replaces some assumptions from prior work on the mathematical model of customer preferences with actual data from a survey to validate the prior work. The results confirm the feasibility of the DR aggregation approach in achieving profits for the aggregator while considering the comfort of the participating customers.

6.2 Introduction

The 2007 Energy Independence and Security Act (EISA07) of the 110th United States Congress introduced the Smart Grid Initiative as the grid modernization drive in the U.S. Under this directive, the Smart Grid included the integration of demand side resources, DR, renewable resources, and smart appliances and customer devices [55]. The integration of diverse and prolific resources into the electricity distribution system—a hitherto ignored realm of relative modernization in the electricity grid—offers the potential for improved system flexibility while increasing the system complexity.

Motivated by the Smart Grid Initiative for enabling an active participation by informed end-users of electricity, an aggregated Smart Grid resource allocation (SGRA) approach is proposed in [18]. However, in [18], the smart appliances involved in the proposed optimization framework are randomly created and their characteristics (e.g., start times and availability periods for rescheduling) are set arbitrarily. Due to its essentiality for the work presented in this chapter, a section is dedicated to explaining the SGRA at an appropriate depth—the interested reader is pointed to [18] for a more detailed description of the SGRA. Even though residential participation in DR programs could achieve 45% of peak load reduction for programs representing 17% of DR potential, only 10% of residential customers are willing to participate [84]. Reducing the impact of allowing appliances scheduling on customer's comfort is a key factor for the success of such programs. Monetary incentives may not be enough for ensuring customers' satisfaction, and the sustainability of these incentives are not clear in the long term [84]. The literature is rife with studies that address the appliance scheduling problem without considering the comfort level of participating customers [85], [86], [87]. Beside the common objective of achieving financial savings to participating customers in DR programs, several studies integrated another objective for minimizing the discomfort caused by appliances scheduling [88], [89], [90].

In this chapter, we extend the previous SGRA approach in [18] by adding rescheduling constraints for home appliances based on usage characteristics as to increase customers' comfort level while enabling financial savings. Data from an actual survey on preferences of residential customers in the US for operating home appliances is presented in [91]. The survey involves 1023 participants from various geographical areas in the U.S. and shows a preference-based prioritization mechanism for home appliances in summer and winter seasons. The purpose of the work in [91] is to inform designers of DR program such as the abovementioned SGRA approach. Our work here presents a simulation-based study to integrate the results of the survey from [91], particularly, the start times of three commo home appliances into the SGRA from [18] and verify the effectiveness of the latter when randomized synthetic data is replaced with realistic data. Furthermore, new constraints for rescheduling these appliances, with the intent of enhancing customer comfort, are introduced. That is achieved by determining rescheduling periods for each appliance instead of rescheduling appliances to random times through the day as the case in [18]. The key contribution of this manuscript is the incorporation of real-world information to extend the validation of the SGRA method.

6.2.1 Load Aggregation Approach

The SGRA approach is a load shifting technique run by a third-party for-profit market entity, namely, the aggregator, as a DR program in the residential sector. The aggregator is involved in arbitrage between the system operator and the residential electricity customers. The aggregator uses a heuristic optimization framework to reschedule some participating smart appliances to other periods with the objectives of maximizing the aggregator's profit position and to reduce the system peak demand. The reschedule of the participating assets is determined one day in advance for enabling seamless participation in day-ahead markets. To encourage consumers to participate, the aggregator offers a dynamic pricing called customer incentive pricing (CIP) that is designed to be competitive with the forecast utility pricing for retail electricity sales.

By collecting information on the schedulable smart appliances characteristics in a distribution system, the aggregator in [18] implements a heuristic optimization to determine a new schedule for a set of the schedulable smart appliances and the CIP. The aggregator's position for profits in the electricity spot market is as follows: i) to promote customer participation, the aggregator offers a CIP that must be lower than the utility pricing during rescheduled times to justify the rescheduling discomfort for consumers; ii) the aggregator aims to reschedule appliances—committed by customers that choose the CIP—away from peak times; iii) consequently, the aggregator offers demand reduction and sells it to the system operator during peak times when spot market electricity prices are expected to be the highest; iv) the aggregator reschedules the committed appliances to other periods of lower spot market prices (this means the aggregator must buy energy to supply its participating customers); and v) the customers pay the aggregator the CIP rather than the utility prices. If the CIP is priced appropriately, this position should realize savings for customers and revenues for the aggregator.

In [18], the authors used a genetic algorithm in the SGRA framework to generate the CIP and the day-ahead appliance schedule. Using 5,555 residential customers, 56,642 schedulable appliances over a 24-hour period, and real-world pricing data, the SGRA approach was demonstrated via simulations to yield profits for the aggregator while performing peak reduction. However, the work in [18] did not use real data of appliance usage (i.e., appliances types and start times); rather, statistical and probabilistic models were used.

6.2.2 User Preferences Prioritization for Home Energy Management System

Reference [91] presents data from a survey of 1023 responses for a multi-criteria decision-making approach to identify user preferences in the residential sector. The objective of the study in [91] is to determine the set of home appliances most likely to be offered by residential customers for DR programs that aim to reduce the system peak load during winter and summer seasons.

The study in [91] prioritizes customers' preferences for several home appliances to be used in designing energy management programs. The prioritization method considers a set of criteria including functionality, cost, and carbon emissions. The survey participants were mostly from the contiguous states in the U.S.; note that the authors of [91] describe the limitations of the data including a caveat against treating the data as nationally representative. The results are educational to the design of energy management systems for enabling DR programs as the case in this chapter, which endeavors towards that goal.

6.3 Problem Statement

Here, the prioritization of customers' preferences for home appliances from [91] is utilized to inform the characteristics of reschedulable appliances that participate in the SGRA approach performed by the aggregators in [18]. The incorporation of actual data is to show that the SGRA approach can achieve profits and peak demand reduction, not just with theoretical assumptions from [18], but also with a large set of real data. Hence, data from the survey in [91] corresponding to three home appliances—the dishwasher, the washing machine, and the clothes dryer—are considered here. These appliances from the survey are chosen for consideration because of their flexibility in operation hours and their uninterruptible nature of operation [92]. Table 6-1 shows the characteristics of these appliances derived from the survey data in [91].

Table 6-1: Schedulable appliances charecteristics [91]

Appliance	**Penetration level (%)**	**Rated power (kW)**	**Duration (hour)**
Dishwasher	67	0.3	1
Washing machine	85	0.665	1
Dryer	80	5.5	1

The penetration percentages of the appliances represent how many of the survey participants own these appliances. Based on the penetration percentages of the appliances shown in Table 6-1, 12,888 reschedulable appliances are distributed among the 5,555 customers of the original case; this contrasts with the randomly created 56,642 reschedulable appliances used in [18]. The 12,888 reschedulable appliances used in this study represent only 6.4% of the total load for the 5,555 customers in the system. In [91], the 1023 participants polled indicated the (typical) start times for the abovementioned three appliances; this information is depicted in Figure 6-1, Figure 6-2, and Figure 6-3 for dishwashers, washing machines, and dryers, respectively. This data is incorporated in the SGRA approach. In this study, the schedulable appliances that are randomly created and originally used in the SGRA approach in [18] are omitted and replaced with the 12,888 appliances described here.

In addition to employing the usage data of each appliance, rescheduling constraints are added to lessen the inconvenience of customers from participating with the aggregator. Each appliance type has a unique constraint depending on its task. For instance, a dishwasher may be delayed from its intended start time without affecting the expected task of dishwashers, which is washing used dishes after meals. Therefore, rescheduling a dishwasher to a random time in the day, as in the original case, may cause significant inconvenience for its owner.

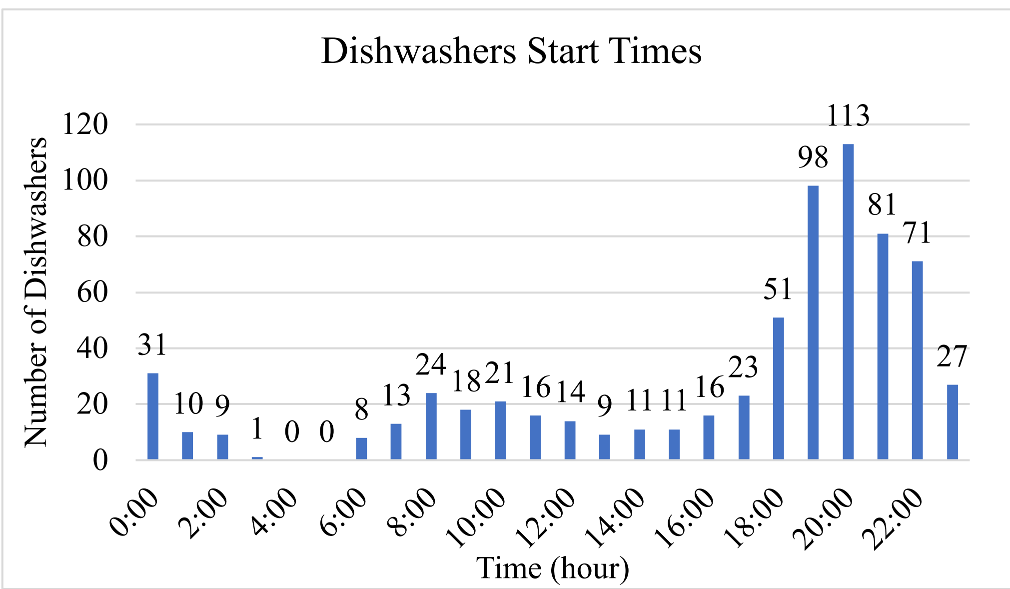

Figure 6-1: Intended start times of dishwashers at each hour through the day from the survey [91]

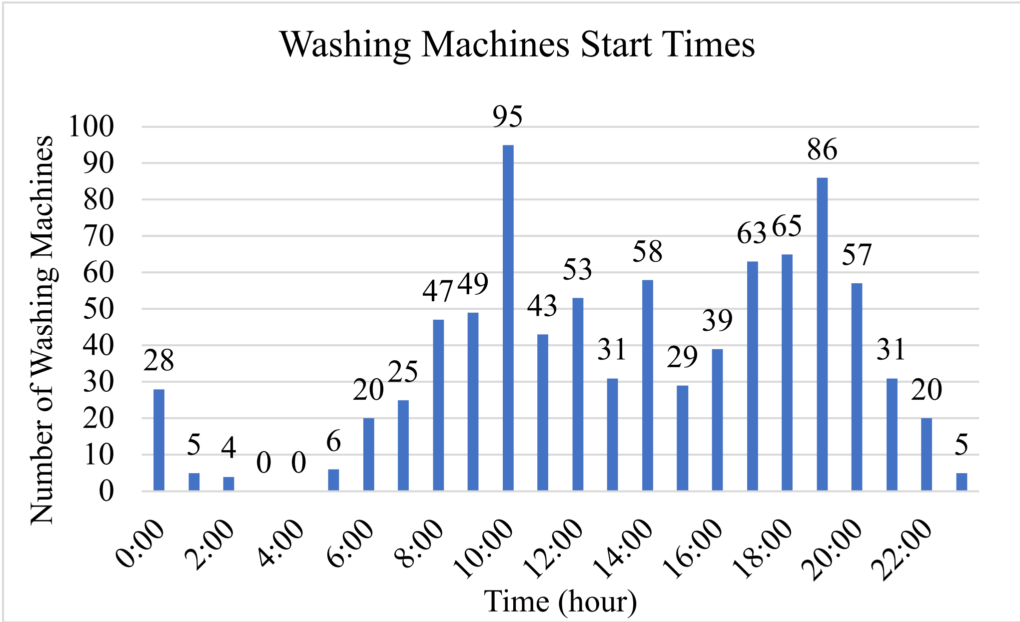

Figure 6-2: Intended start times of washing machines at each hour through the day from the survey [91]

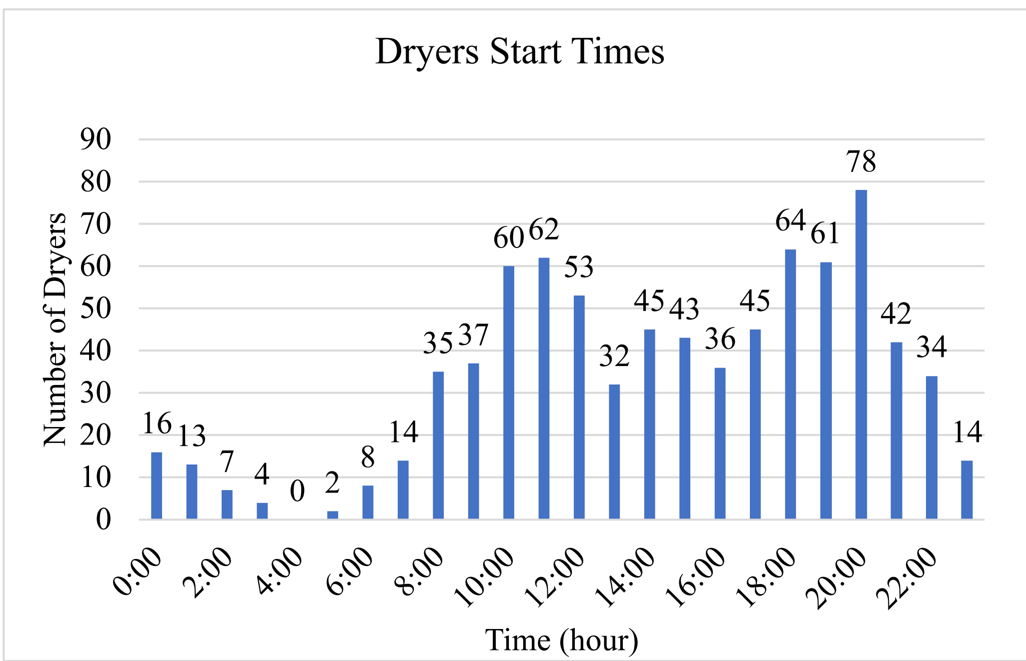

Figure 6-3: Intended start times of dryers at each hour through the day from the survey [91]

The following constraints are added to the SGRA optimization for rescheduling the 12,888 reschedulable appliances from the three appliance types mentioned above. Firstly, the period for rescheduling dishwashers is *subjectively* set to five hours after the originally intended start time.

That is, dishwashers are to be rescheduled to a time no later than five hours from the originally intended start time. This constraint is modeled mathematically as in (1), where t_{start}^{dish} is the originally intended start time of a dishwasher, and t_{resch}^{dish} is the rescheduled start time of that dishwasher.

$$t_{start}^{dish} < t_{resch}^{dish} < t_{start}^{dish} + 5 \qquad (1)$$

Secondly, washing machines and dryers must be rescheduled chronologically to account for their interrelated functions. In addition, for the comfort of customers, the laundry appliances are rescheduled in a *subjectively* set period of six hours around the originally intended start times set by the owners. Equations (2) and (3) account for these two constraints pertaining rescheduling a washing machine and a dryer for an individual customer, where t_{start}^{w} the originally intended start time of a washing machine, t_{resch}^{w} is the rescheduled start time of that washing machine, and t_{resch}^{d} is the rescheduled start time of a dryer of the same customer who owns the related washing machine.

$$t_{start}^{w} - 3 < t_{resch}^{w} < t_{start}^{w} + 3 \qquad (2)$$

$$t_{resch}^{w} < t_{resch}^{d} \qquad (3)$$

The spot market energy prices and the utility prices are inputs for the aggregator. The utility pricing and spot market pricing information used in the simulation are real data from a randomly selected day (Wednesday July 1, 2020), acquired from ComEd residential RTP [93] and PJM [94], respectively. This data includes forecast and actual hourly prices for the utility and spot market. We choose PJM and ComEd to be in line with the base case in [18].

6.4 Results

The aggregator achieves a reschedule for a set of 12,888 schedulable appliances by performing the SGRA approach. Figure 6-4 shows the accumulative load of the schedulable appliances before and after performing the SGRA approach for a 24-hour period. To maximize its profits, the aggregator reschedules appliances from peak hours when spot market prices are high to other times when spot market prices are lower according to the rescheduling constraints in (1)–(3). As the schedulable load is part of the total load, the new schedule affects the total load as well. Figure 6-5 shows the total load including schedulable and base loads of the entire 5,555 customers before and after performing the SGRA approach. 53% of the schedulable load is moved from peak time to the other; this equals 4.2% of the total peak load on the system that is shifted. Note that this effort in peak reduction causes the base loads during off-peak to increase by 6.7%.

The aggregator also offers CIP for the participating customers. Figure 6-6 shows the CIP offered by the aggregator compared with the forecast spot market price and forecast utility price. The forecast aggregator profit, which is the final objective value, achieved by the SGRA optimization is $484.37. When the actual utility and spot market pricing are used for evaluating the actual profit of the aggregator, the schedule determined by the SGRA optimization resulted in an actual profit of $450.52. This reduction in actual profit from forecast profit is because the actual spot market pricing at peak hours is lower than forecast as shown in Figure 6-7, which leads to a decrease in the actual profit.

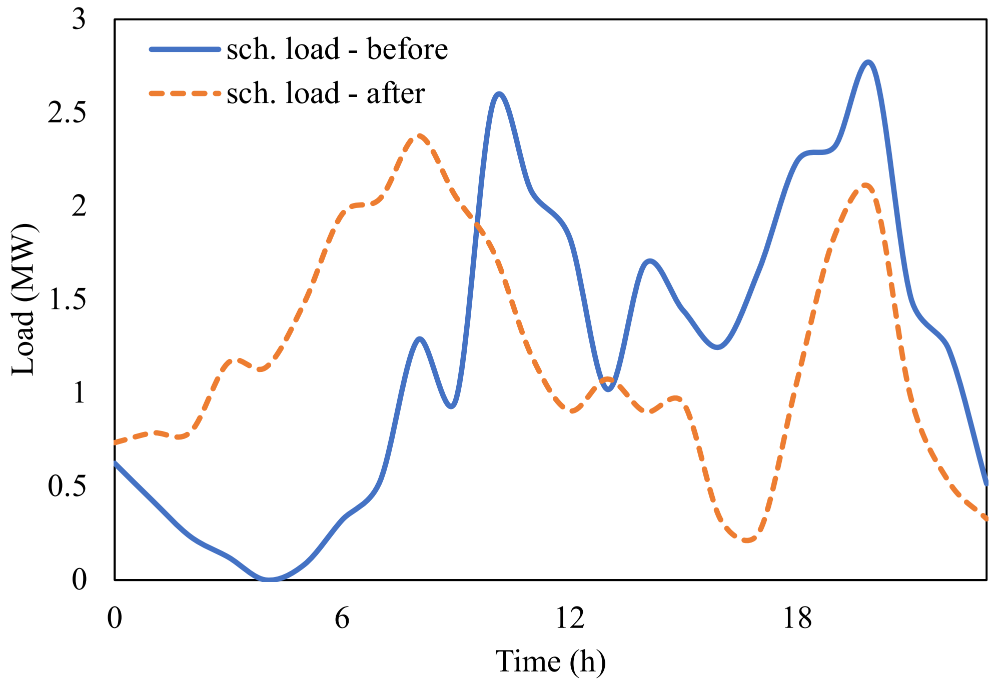

Figure 6-4: Schedulable load profile before and after aggregation

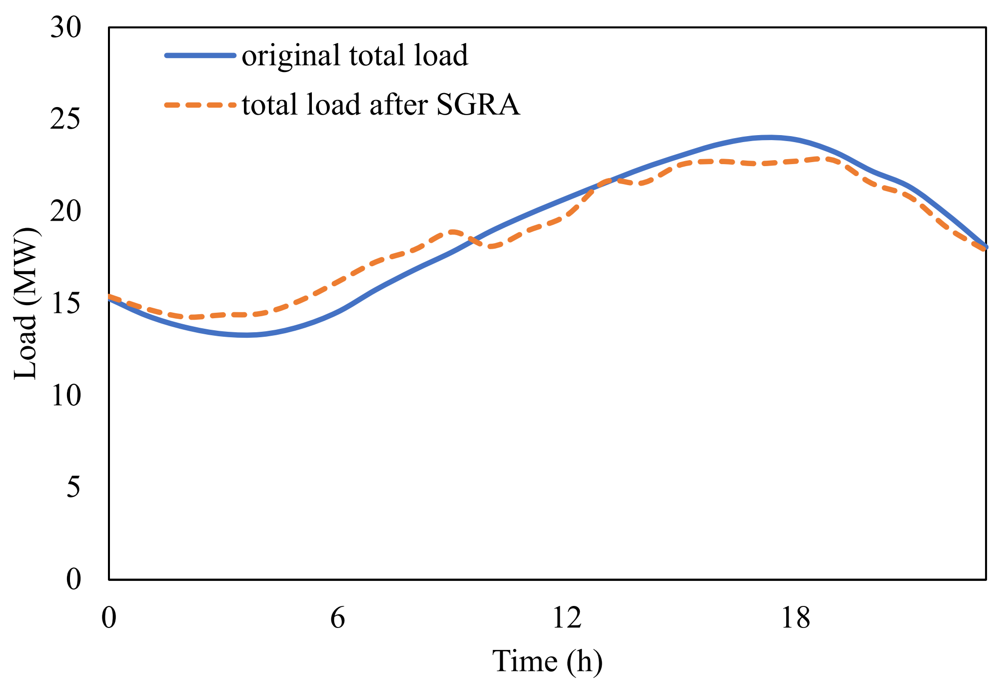

Figure 6-5: Total load profile before and after aggregation

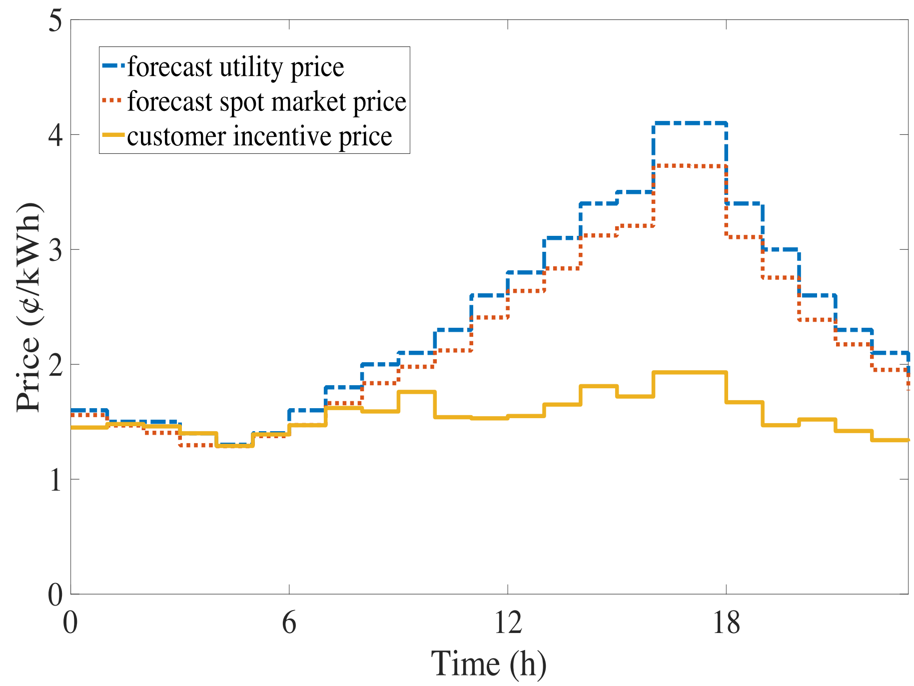

Figure 6-6: Forecast utility price, forecast spot market price and CIP

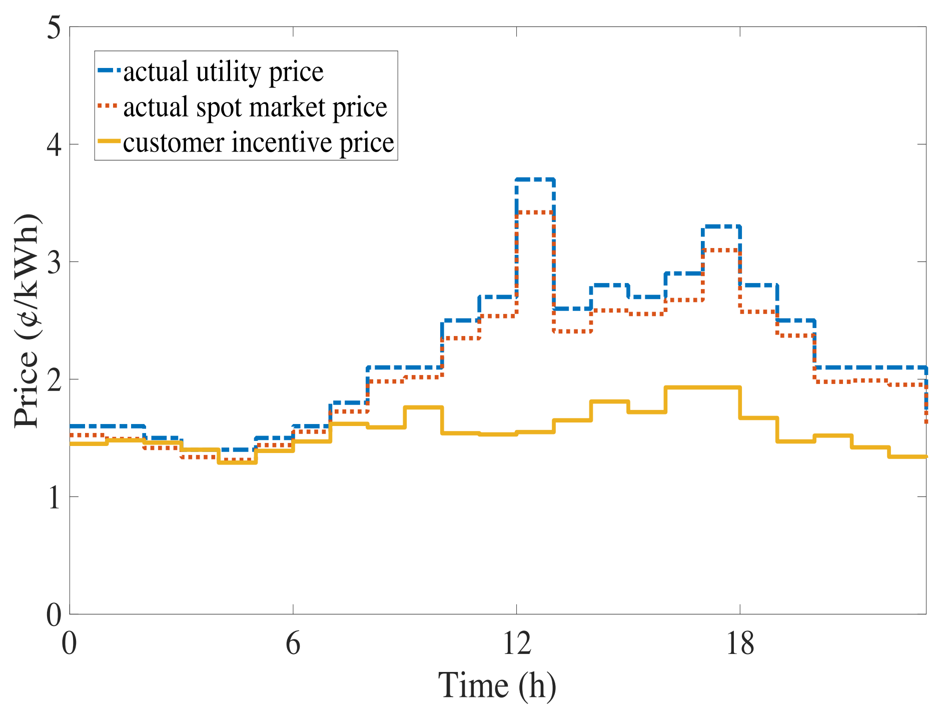

Figure 6-7: Actual utility price, actual spot market price and CIP

6.5 Conclusions

Data on three home appliances from an actual survey are used to inform the optimization framework of the SGRA approach. Unlike the base case of the SGRA approach, which uses random data for the schedulable smart appliances, the use of real data from the survey in [91] indicates the extended reach of SGRA for practical applications. Using real data about the behaviors of customers on operating smart appliances not only supports the feasibility of the SGRA approach but also allows the SGRA program designer to account for the comfort of the participating customers. This also takes into consideration the task of each appliance when rescheduling it. Dishwashers may be rescheduled as late as five hours after the usual start time because this kind of appliance is mostly correlated to customers' habits in consuming food and then doing dishes. Hence, delaying the use of dishwashers a few hours is more convenient than rescheduling it to a random hour through the day. In addition, setting random rescheduled start times for a dryer does not account for the appliance's sequential nature related to another appliance, i.e., the washing machine; not considering such practical constraints may cause significant discomfort for participating customers and introduce unreliable results in expected DR.

CHAPTER 7

CONCLUSIONS AND FUTURE WORK

7.1 Overview

In this chapter, a number of conclusions are presented on the dissertation research as well as the associated results. In addition, this chapter discusses future issues that are directly linked to the research included in this dissertation. This chapter is organized as follows: Section 7.2 concludes the work presented in chapter 3 on the integration of negawatt trading with the SGRA approach; Section 7.3 concludes on the results of the study presented in chapter 4 on the integration of the SGRA aggregators with carbon taxation into electric power systems; Section 7.4 presents conclusions on the issues related to studying the long-term effects of applying carbon taxation in electric power systems; from the study in chapter 5 about the relationship between the SGRA aggregator's performance and utility pricing mechanisms is presented in section 7.5, and section 7.6 concludes the work related to chapter 6 about the incorporation of rescheduling constraints into SGRA approach using actual appliances usage data.

7.2 Integration of SGRA Approach into Negawatt Trading

In chapter 3, a new method was presented for the problem of power supply-demand adjustment in real-time electricity market, which was designed to be an hour-ahead market after gate closure of the day-ahead market from the previous day. As renewable energy resources increase in electricity markets, higher levels of intermittency, and associated uncertainty, occur on generation side. That uncertainty further increases the deviation ranges of generation from forecasted load—which, too, is an uncertain factor. Therefore, DR is proven to have potential in addressing the integration of intermittent resources.

Motivated by the abovementioned elements, a relationship between the ISO and DR aggregator was designed for the power supply-demand adjustment operation. The proposed power adjustment method includes more resources beside balancing generators, which is traditionally used for adjusting generation to match the required demand. These resources include demand reductions set to the DR aggregators and changes in power flows in the tie-line connecting areas in electric power networks from what scheduled in the day-ahead market. The applicability of the proposed method is verified by applying it to a 4-area power network. The results showed that distributed resources participating in a real-time market can successfully balance the demand with the supply with minimal balancing costs. Perhaps, the most important takeaway is that the imbalance due to rewindable energy resources and their intermittency can be dealt within an area without impacting the area control error by changing the tie-line flows.

The method in chapter 3 determined the amount of DR resources that DR aggregators are required to make available by interacting with individual customers in different areas of the power network. Nevertheless, the chapter does not address the relationship between DR aggregators and customers and how the aggregator provides the required DR resources to the ISO. The relationship between DR aggregator and residential customers was presented in the SGRA approach and was widely demonstrated in chapter 4.

7.3 Integration of DR Aggregators with Carbon Taxation

Chapter 4 presented the integration of multiple DR aggregators into a transmission level power system. Each aggregator dealt with simulated residential customers for rescheduling smart appliances using the SGRA approach. The SGRA approach-based aggregators offered incentive pricing to participating customers to reschedule their smart appliances to a random time during the day. The objective of the aggregators was to maximize profits, thus rescheduling customers' appliances away from high-prices peak times and selling that peak demand reduction to the ISO. That describes the relationship between DR aggregators and participating customers at distribution network level. However, DR aggregators provide benefits to wholesale electricity markets. That is, they provide demand reductions during peak hours, thus reducing the CFs of expensive peaking units and lowering electricity prices at peak hours. Therefore, DR aggregators influence the dispatch of generation units and thus influence electricity prices. In chapter 4, the integration of the SGRA approach at a fully defined power system simulated using the RBTS system was presented. This showed how SGRA-based aggregators at different load buses and areas in the network can be integrated into a DRX market in a day-ahead time frame. The integration of aggregators can supersede the utilization of peaking units in providing peaking services at peak hours. This was shown to cut down on the GHG emissions of peaking units.

In tandem with the integration of SGRA-based aggregators, carbon taxation for fossil-fuel based generation was applied on fossil-fuel based units in the system to reduce GHG emissions and thus support the emergence of other types of generation. A carbon tax function was applied for fossil-fueled generators based on emission rates for electricity production. The carbon tax function is time-dependent, so the study simulates the imposition of carbon tax for the current year of 2020. The levied carbon tax on coal and natural gas generators affected their dispatch under OPF because these generators pushed closer to extra-marginality in the market and less competitive than other types of power plants. Emissions reductions achieved by the applied carbon taxation were quantified in chapter 4.

The combination of the SGRA approach for DR with the carbon taxation showed economic and environmental benefits. The environmental advantages were shown in reducing the CFs of both the peaking and base-load serving fossil fueled units, while the economic advantage came from the SGRA approach that achieves a significant reduction in the output of peaking units, thus reducing the MEP. However, this reduction in peak energy use was deferred to other off-peak times when fossil-fueled base load units may continue to emit pollutants.

In summation, applying carbon taxes on all fossil-fueled generators achieves reductions in their dispatches, thus realizing holistic reductions in CO_2 emissions. However, the downside of solely applying the carbon taxes is considerably affecting electricity prices; but, that impact on electricity prices is alleviated when the carbon taxes are combined with the SGRA approach as indicated by the MEP from the simulations.

The proposed carbon tax function in chapter 4 was designed to increase by a compound growth rate of 5% annually, which was expected to further affect fossil-fueled generators. This annual growth of taxation was set to further suppress or mitigate the imminent danger of climate change as it is expected to contribute in limiting the global temperature increase at 2.5 ℃. The effect of the increasing taxation is to be studied in future work; however, section 7.4 briefly presents some issues around the long-term effect of carbon taxation.

7.4 Long-Term Effect of Carbon Taxation

A recent report shows the physical signs of the anthropogenic climate change including increasing heat in ocean and land, melting ice in both the Arctic and the Antarctic, rising sea levels, and causing acidification ocean waters [95]. The report also shows that GHGs reached record levels in 2018. It is evident that the risks posed by anthropogenic climate change are dire, and it requires collaborative efforts by the international community to mitigate it [96]. The electricity sector is among the biggest contributors to the global problem of climate change, mainly by using fossil fuel-based generation units. The fossil fuel sources rates globally used for electricity production is 38% of coal, 23% of natural gas, and 2.9% of oil [97]. The challenge in bulk electricity markets is finding incentives in order to encourage more renewable energy sources and make them competitive to fossil-fuel generators. As a solution, carbon price shows promising potential in spite the fact that finding the true cost of carbon tax is complicated and hard to quantify with any accuracy [98]. However, studies show that carbon taxation plays a major role and proves effectiveness in achieving less fossil fuel-based generation; thus, achieving less CO_2 emissions [99].

One of the problems of imposing carbon tax on electricity producers is its effects on electricity prices. Carbon taxes tend to increase electricity prices in deregulated electricity markets. In [99], a study shows that retail electricity prices tend to rise due to decarbonatization levies and taxes to a large extent. To a smaller extent, the study also showed that the increasing penetration of renewable energy sources generation technologies contributes to increasing the electricity prices. This problem may be alleviated by using the SGRA approach in tandem with carbon taxation as explained in chapter 4.

In chapter 4, carbon taxation achieves reduction in fossil-fueled generators of the RBTS test system including coal-fired generators, combined cycle natural gas generators, and natural gas-fired generators. That reduction in the dispatch of fossil-fueled generators resulted in corresponding reduction of CO_2 emissions. The proposed carbon tax function is time dependent. That is, the carbon tax is set to increase by 5% annually starting from 2020 to 2050. Chapter 4 quantified the reflection of imposing carbon taxation on fossil-fueled generation only in present time in 2020. However, the long-term effect of imposing carbon taxation on fossil-fueled production is complex as it needs predictions for load and generation growths. In addition, the aging factors of current fossil-fuel based generators must be taken into consideration. Another influential factor for predicting the effect of applying carbon taxation is variable regulations by government policies.

7.5 DR Aggregators' Performance with Different Pricing Mechanisms

Chapter 5 presented a simulation-based analysis for the influence of utility pricing mechanisms on the performance of SGRA-based aggregators in terms of daily achieved profits as well as shifted peak demand during peak hours. The utility pricing mechanisms considered include RTP, TOU pricing, and fixed tariffs. The importance of the study stemmed from the fact that SGRA-based aggregators run in competition and parallel to utilities, so showing how utility pricing mechanisms affect the profitability of aggregators leads to enhanced aggregator's management.

The results showed that aggregators made the largest peak load reduction when integrated with utilities applying RTP. However, they made the least profits in comparison to the types of pricing systems. On the other hand, the aggregators that are integrated with utilities offering fixed tariffs made the most profits, but they bring the least peak load reduction. As for the aggregators with TOU pricing-based utilities, they made more profits than the aggregators with RTP pricing-based utilities, but less than the aggregators with fixed tariff pricing-based utilities. The fact that aggregators with TOU pricing utilities made less profits than those with fixed tariff pricing utilities is due to the considerably lower off-peak prices for TOU pricing. That forces the aggregators to offer even lower prices to incentivize customers for participation, which directly affects the revenues of the aggregators. Caveat lector the above conclusions are empirical and based on the data used in the study.

7.6 Incorporation of Rescheduling Constraints into SGRA Approach by Using Actual Data

The base case of the SGRA optimization in [18] randomly created a set of reschedulable home appliances with random periods for rescheduling these appliances by the aggregator. So, Chapter 6 was dedicated to incorporating survey-based data of three home appliances into the SGRA approach. In addition to the incorporation of the appliances data form the survey, new rescheduling constraints for each one of the three appliances were integrated into the SGRA residential DR aggregator that runs a resource allocation for peak demand reduction in a notional electric distribution system. The integration of these constraints into the resource allocation approach was to alleviate the inconvenience of the participating customers due to rescheduling their home appliances. The results confirmed the feasibility of the constrained SGRA approach in achieving profits for the aggregator while considering the convenience of the participating customers.

The incorporation of real data from the survey in [91] indicated the extended practicality the SGRA approach using specific home appliances. These appliances are dishwashers, washing machines, and dryers. Using real data about the behaviors of customers on operating smart appliances not only supports the feasibility of the SGRA approach but also allows the SGRA program designers to enhance the comfort levels of the participating customers by adding rescheduling constraints for each appliance. When designing these rescheduling constraints, designers take into consideration the task of each appliance. For instance, in the presented case in chapter 6, dishwashers may be rescheduled as late as five hours after the usual start time because this kind of appliance is mostly correlated to customers' habits in consuming food and then doing dishes. Hence, delaying the use of dishwashers a few hours is more convenient than rescheduling it to a random hour through the day. In addition, the rescheduled start times for dryers cannot occur chronologically before the rescheduled start times for washing machines due to the fact that washing must be done before drying.

7.7 Future Work

DR applications are the crux of this dissertation. As in chapter 3, the power supply demand adjustment problem in real-time is solved using DR aggregators beside power flow exchanges and balancing generators. The involvement of DR resources made available by DR aggregators is beneficial for the gird not only for the faster response to supply-demand mismatches but also for the lower costs than the conventional method for solving this problem, which is using balancing generators run by balancing authorizes. However, the presented method is chapter 3 does not propose a trading mechanism for power flow exchanges among areas. That is, each area has independently its own generation capabilities, and the participation in power supply-demand balancing would not be convincing unless there is a proposed mechanism proving the profitability of the participating areas. That should be addressed in future work.

Chapter 4 combines a DR program with the introduction of carbon taxes on fossil-fuel generators. The combination of the two methods proves its feasibility in reducing the dispatch of fossil-fuel generators in the system, thus reducing the accompanying CO_2 emissions. It also proves its practicality in mitigating the increases in energy prices caused by applying carbon taxes by utilizing SGRA approach. The presented work in chapter 4 is dedicated to study the effect of applying both methods in the year of 2020 despite the fact that the presented carbon tax function is a time-dependent function from 2020 to 2050. The long-term effects on CO_2, electricity prices, and generation profiles is to be studied in future work.

In addition, Chapter 5 presented an empirical study to find the relationship between different types of utility pricing mechanisms and the performance of the SGRA-based aggregator. However, future work may need analytic approaches to conclude more generic results.

Finally, chapter 6 added scheduling constraints for appliances involved in the SGRA approach. The purpose of these constraints was increasing the comfort level for customers participating in the program. Even though the constrained case in chapter 6 confirmed the feasibility of SGRA with higher comfort level for customers, it did not include a metric for customers' comfort level to compare the base (i.e., original) case and the constrained case in chapter 6. In future work, a comfort level metric for participating customers should be applied in SGRA approach.

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