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Cloud-based energy management service: Design, analysis, and realization

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Cloud-based energy management service: Design, analysis, and realization

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DEDICATION

To my beloved family for the endless support and encouragement.

—Yu-Wen Chen

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ABSTRACT

With the aroused attentions on promoting renewable energy and the increasing penetration of distributed energy resources (DER) and the electric vehicles (EVs), providing the energy management tools efficiently for operating DERs and EVs grid-friendly and attracting customers to involve the management have become the important issues. An extensive cloud-based framework is firstly proposed to provide the energy management as a service (EMaaS) for customers (i.e., DERs owners). Customers who are involved in the same EMaaS form the "*community*" to trade their produced renewable energy virtually among others. By facilitating the DERs, storage systems, and the customers' trading choices within the same community, incentives are maximized as the global cost is minimized and renewable energy integration is enhanced as the renewable energy consumption is stabilized by the proposed EMaaS for each community. To further attract customers not only involve in controlling their consumption patterns but also participate actively, and operate EVs and DERs within the community grid-friendly, the fair demand response with the EV is secondly realized for the cloud-based energy management service (F-DREV). The choices of electricity usage and trading are combined to further minimize the global cost for each community while distributing incentives fairly to the individual customer. The cross-community interaction (XCI) and adjustment (XCI) are thirdly proposed for the cloud-based energy management. XCI minimizes the global costs for the collaborated communities and is performed in the distributed fashion to overcome the privacy concern and the difficulty for handling the large-scale data. XCA enhances the efficiency of XCI under uncertainty, where the overwhelmed data exchanging and the computations can be significantly reduced.

CHAPTER 1. INTRODUCTION

Reducing greenhouses gasses by promoting renewable energy has become an important goal for many countries in recent years to ease the severe climate changes. How to encourage companies and residents to adopt both large-scale renewable generators (such as solar parks, wind farms) and distributed rooftop photovoltaic (PV) power, and be able to simultaneously enhance the integration of these non-dispatchable distributed energy resource (DER) without bringing challenges (such as reserve capacity, scheduling, and load management) caused by the fluctuations and uncertainties to the entire power grid becomes a critical issue. It is achievable with proper managements and novel trading strategies that could provide incentives to involved customers and efficient control to the entire power grid.

In this thesis, we firstly introduce the state of the art for the electricity market in chapter 2. The wholesale electricity market and the distributed electricity market are discussed. The area that this thesis is related is also pointed out.

Following with the discussion of the electricity market, this thesis proposed a cloud-based framework to provide a customer-oriented energy management as a service (EMaaS) for "*green communities*", which are formed as virtual retail electricity providers (REP) by involved DERs providers. While the green communities are formed as virtual REP, customers (i.e., involved DERs providers) are able to virtually trade their produced renewable to each other, and be able to benefit mutually. EMaaS is an extensive framework and also a business model for renewable energy integration. Incentives are maximized as the global cost is minimized and renewable energy integration is enhanced as the renewable energy consumption is stabilized by the proposed EMaaS for each green community. A linear programming model is formulated for EMaaS. [1]

This thesis secondly introduced the demand response and the charging scheduling of electric vehicles (EVs) are realized for the cloud-based energy management service. With the combination of electricity usage choices and trading choices, the proposed fair demand response with electric vehicles (F-DREV) is able to further minimize the global cost for each community while distributing incentives fairly to the individual customer via a binary linear programming model. The fairness in F-DREV is proposed as "customers with higher participation level can reduce individual cost more than other customers with lower participation level." It is attainable by customizing trading prices for each customer base on his/her fairness index. F-DREV attracts customers not only to involve in controlling their consumption patterns but also participate actively, and allows EVs and DERs within the community operate grid-friendly by smoothing the fluctuated penetration of EV loads and production capacities from DER. [2]

The distributed large-scale interaction and adjustment are proposed for the cloud-based energy management in the third part of the thesis. The cross-community interaction (XCI) minimizes the global costs as maximizing the incentives for customers within all the collaborated communities over the given time period. XCI is performed in the distributed fashion to overcome the privacy concern and the ability, scalability, and efficiency of the allocated computing resources for handling the large-scale data. It can be solved efficiently via the alternating direction method of multiplier (ADMM). The cross-community adjustment is also proposed to enhance the efficiency of XCI for the cloud-based energy management service under uncertainty. The overwhelmed data exchanging and the computations can be significantly reduced without rerunning the management frequently.

[1] This chapter is published in Smart Grid, IEEE Transaction on, vol.6, no.6, pp.2816-2824, Nov. 2015

[2] This chapter is published in Smart Grid, IEEE Transaction on, vol.PP, no.99, pp.1-1, doi: 10.1109/TSG.2016.2609738

The summary and the future work are discussed in the last part, and the remainder of this thesis is organized as follows. The state of the art for the electricity market is discussed in chapter 2. The "EMaaS: Cloud Based Energy Management Service for Distributed Renewable Energy Integration" is introduced in chapter 3. The "Fair Demand Response with Electric Vehicles for the Cloud Based Energy Management Service" is discussed in chapter 4. The distributed large-scale interaction and adjustment are proposed in chapter 5. Summary and future work are discussed in chapter 6.

CHAPTER 2. STATE-OF-THE-ART: ELECTRICITY MARKET

This chapter presents the introduction of the state-of-the-art for the current electricity market and how the proposed work in this thesis relates to the current practice.

A system of electricity market [3] enables the purchases, sales and short-term trades of electricity (both power and energy) with the main attributes that include the various spectrum of electricity markets (i.e., day-ahead, hour-ahead, and real-time market), markets for both financial and physical (i.e., transmission rights, capacity, reserve markets), and various tradeable commodities (i.e., energy, ancillary services). Purchases are usually performed through bids to buy, and sell through offers. Both bids and offers follow the supply and demand principles to set the price, and the power purchase agreements are the contracts considered private bilateral transactions between counterparties in contracts as the long-term trades.

The entire electricity market can be generally divided into two scales, that is, the wholesale electricity market and the retail market, as shown in the Fig.2.1 following the concept in [4] and [5]. The structure contains the **day-ahead market** and the **real-time market**. Both of these two markets include the **energy** and **ancillary services**, and are arranged according to the **bilateral contracts** and the **power system**. Competing generators company offer their electricity outputs to the retailer or large consumer in the wholesale electricity market, and then the retailer re-price the electricity and take it to the retail electricity market, which depends on the availability of the retail choices within different states [6] and is presented as the dashed box in Fig. 2.1. Large consumers

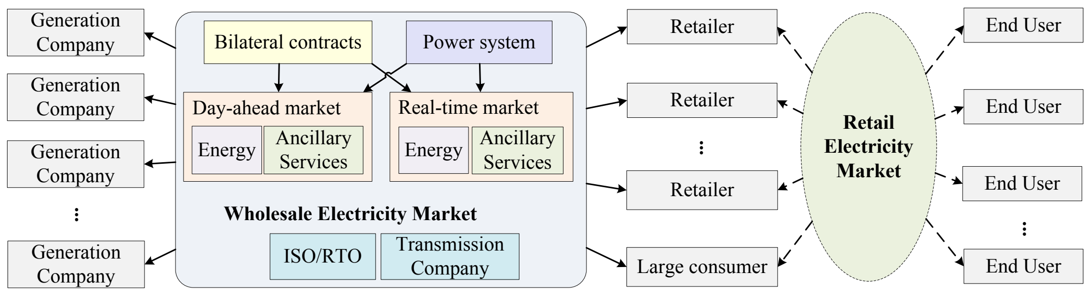

Figure 2.1: The existing general electricity market structure

could either purchase from the wholesale market or from the various retailers in the retail electricity like the end-users of the electricity.

More details for the wholesale electricity market, the distributed electricity market and the domain of this thesis are discussed in the following sections.

2.1 Wholesale electricity market

The wholesale electricity market has the objective to promote economic efficiency and lower delivered energy costs, maintains power system reliability, mitigates significant market power and increases the choices offered to wholesale market participants. Trades in the wholesale market occur within a multi-state interconnection as the interstate sales. Depending on the nature of the sales, the wholesale market is regulated across the country in regions expect the ERCOT, which functions as an exception as the entire interconnection lies in a single state, Texas. Split structure exists within the regional wholesale markets, where a number of regions organize their markets under an independent system operator (ISO) or a regional transmission organization (RTO). According to the Federal Energy Regulatory Commission, the latest existing regional wholesale markets are shown in Fig. 2.2 [1], and markets within the United State are listed in the following.

1. ISO New England

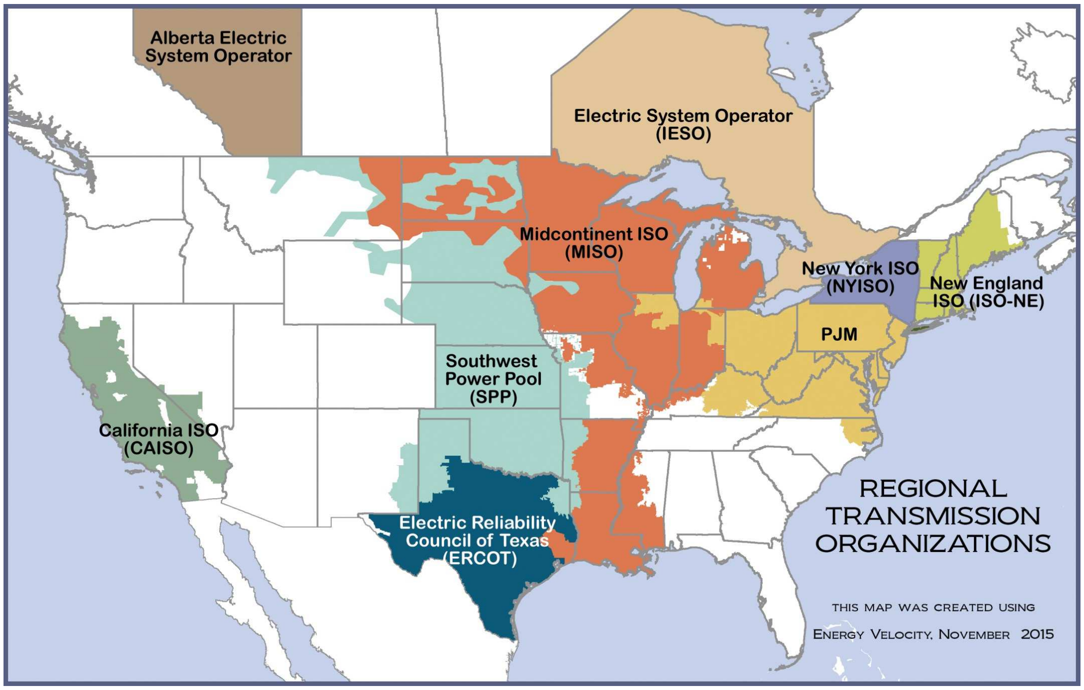

Figure 2.2: Regional Organization Map from FERC [1]

2. New York ISO
3. PJM (Mid-Atlantic, a portion of the Midwest)
4. Midwest ISO
5. Southwest Power Pool
6. ERCOT (most of Texas)
7. California ISO

The ISO/RTO was authorized to administer wholesale markets for the sale of electric energy (both day-ahead and real-time purchases), electric power capacity, and ancillary service (as we mentioned in the beginning paragraph of this chapter). They decide which generators will run and at what levels, grant the transmission services, and run the billing system for payment for power with the prices set through bilateral exchanges but determined by the ISO/RTO [7].

The **Day-ahead market** and the **real-time market** are the existing markets that contribute to the the **spot market** in the wholesale electricity market, where a central dispatcher or the broker administer interchange between different utilities and split the savings between both low-cost utility and higher-cost utility. [5]. Both of the day-ahead and the real-time market trade **energy** and the **ancillary services** that include the reserve capacity, load following and frequency regulation, voltage regulation, and black-start capability [8]. The **power system** and the **bilateral trading** arrange outside of those two market, where the bilateral trading determines the price of each transaction via negotiation between two involved parties (i.e., buyer and seller), and is occurred as long as owners of the different electric system were interconnected [9].

The locational marginal pricing (LMP) [10] or nodal pricing are commonly considered as the best approach available for operating large, interconnected power pool efficiently and reliably. LMP is used in the wholesale electricity market to reflect the value of electric energy at different locations, accounting for the patterns of load, generation, and the physical limits of the transmission system. Elements of the LMP include the constraints, the locations, and the marginal pricing, which reflects the cost to serve the next increment of load in a system that is economically dispatched.

2.2 Retail electricity market

The retail electricity market involves the final sale of power from an electricity provider to an end-user of electricity (i.e., consumer). Regardless of whether every state allows retail competition or not, supply for end-user is obtained either through the open, competitive wholesale market, from the utility-owned rate-based generation or some combination of the two [11]. Generally, electricity retail reform follows from electricity wholesale reform, but it is possible to have a single electricity generation company and still have retail competition. That is if a wholesale price can be established at a node on the transmission grid, and the electricity quantities at that node can be reconciled, competition for retail customers within the distribution system beyond the node is possible, such as the German market. End-use customers can choose their supplier from competing electricity retailers.

While the market structures are varied, electricity retailers have some common functions to perform or enter into a contract for to compete effectively. Those functions include the billing, credit control, customer management, distribution use-of-system contract, reconciliation agreement, pool or spot market purchase agreement and the hedge contracts. Competitive retail needs open access to distribution and transmission wires, thus appropriate returns (i.e, the access fee and the regular fee) have to be provided to owners of the wires and encourage the efficient location of power plants. Retail electricity providers (REPs) [12] also have to provide the real-time market analysis to determine return-on-investment for optimizing profitability or reducing end-user cost of goods, therefore, various service plans are developed to promote their customers' participation. Unlike the strategies in the wholesale electricity market, how to provide and design the more flexible service plans to their customer is a critical issue for REPs in the competitive retail electricity market. To attract customer not only involving the energy management (e.g., demand-side management) but also actively use from renewable energy, ***choices*** are the essential factors [13] in retail electricity market.

Several existing schemes are developed to provide incentives to end-user of electricity (i.e., customers) in the scale of retail electricity. Some exist directions are enabling the competitive retail electricity market to allow customers have the choice of choosing various REP, providing the demand response to create the opportunity for customers adjusting their electricity demand according to the fluctuated electricity prices, or accepting the bidding scheme for consumers' devices. Net metering is another existing scheme to DERs owners by providing the buy-back programs for customers' excess generation, and its policy has been well established in the state as shown in Fig. 2.3 [2].

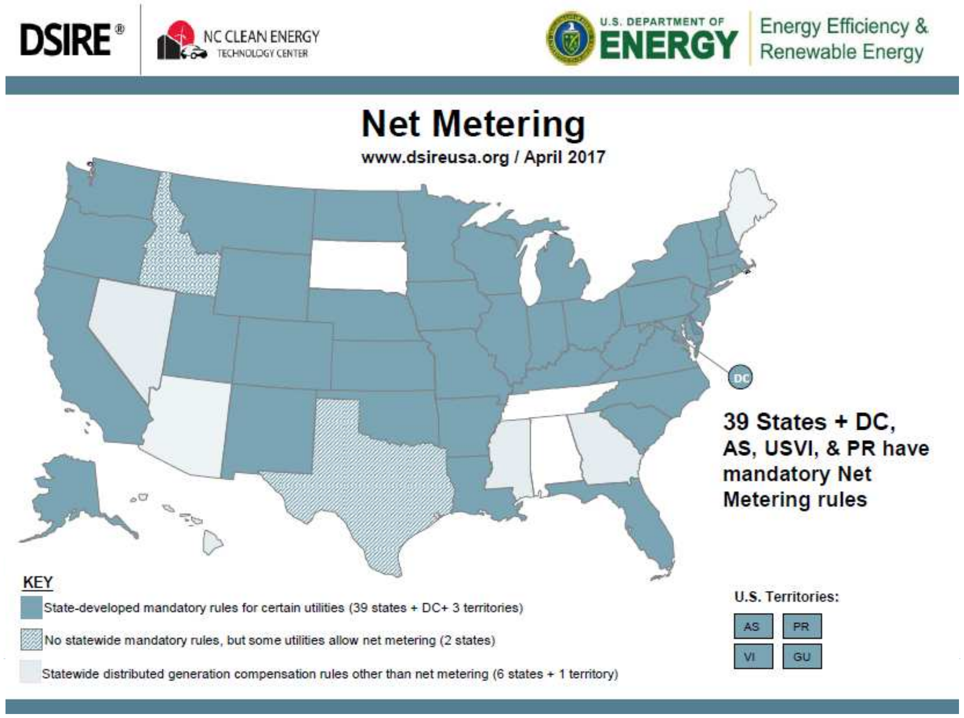

Figure 2.3: Net Metering from U.S. Department of Energy DSIRE [2]

According to the International Confederation of Energy Regulators (ICER), the policy behind the net metering recognizes that energy generated at the point of consumption by the customer is worth at least as much as a unit of energy delivered by the utility to that customer, and that energy is worth more than the traditionally calculated avoided cost of generating the next marginal unit of energy at a remote power plant [14].

2.3 Discussed domain of this thesis

Currently, the electricity may be restricted to wholesale trade only and the retail markets involve electric energy sale directly to the end-users. Yet, recently, the development of retail electricity market arouse a lot of attentions as it is in the transforming process with the new deployed advanced power engineering technologies, such as individual owned distributed energy resources (DER), electric vehicles (EV), or individual storage systems, from the end-users side. In other words, the future electricity market structure

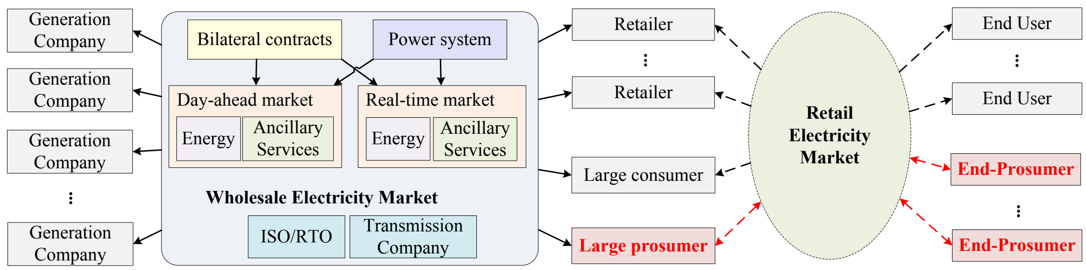

Figure 2.4: The future electricity market structure

could be transformed into the structure shown in Fig. 2.4, where customers with the new role as prosumer (i.e., producer and consumer). Depending on the scale of the owned DERs, customers would be either the large prosumers or the end-prosumer and have the opportunity to act as different roles either in the wholesale electricity market or the retail electricity market, which are denoted as the new appeared red double head arrow in Fig. 2.4. Similar to the large consumer, large prosumers could either purchase from the wholesale market or from the various retailers in the retail electricity, and they could also participate either in the wholesale electricity market as a generation company or in the retail electricity market as a retailer with their energy production. End-prosumer could participate in the retail electricity market following the net metering programs provided by the retailers. Following the concept of the essential factor "choice" in the retail electricity market for customers' participation, a progressive business model has to be developed to adapt and create prosumers' behaviors between the retail electricity market. Moreover, the energy management is also required at the retail level, as without proper management for the emerged DERs and EVs, the fluctuations and uncertainties of uncontrollable and intermittent renewable energy resources [15][16] could bring several potential challenges exist for integrating these DERs and EVs, such as reserve capacity [17] [18], scheduling, load management and forecasting [19].

In the literature, several approaches have been attempted to enhance renewable energy integration. Distributed generations (DG) and their integration attempts [20][21] have been investigated to dispatch bidirectional flows on aged distribution network designed for unidirectional flows. Due to the fact that conventional distribution management systems infrastructure commonly lack the capability of DG dispatching, power grids, and local loads have to passively accept unmanaged DG outputs. In order to provide a managed renewable integration, a cluster of DG installations can be collectively bundled as a virtual power plant (VPP) [22] and operated by a centralized control entity. As the core of VPP, the energy management systems (EMS) of a scheduling coordinator can maximize the cluster profit by managing its distributed energy resources (DERs) while considering their physical positions [23]. Demand response (DR) is also available as an energy management technique from the demand-side perspective. As an important ingredient of the smart grid, DR promotes both market efficiency and operational reliability and is currently evolved in existing programs at different Independent System Operators (ISOs)/ Regional Transmission Organizations, such as California ISO (CAISO) and New York ISO [24]. Microgrid functions autonomously by incorporating localized DGs, storage systems, and controllable load. Microgrid control center optimizes operating states and coordinates components to pursue economic benefits in either grid-connected or stand-alone mode [25]. Multiple microgrids can participate in the market and effectively utilize the DERs through a two level multi-agent systems [26]. According to the above four renewable integration schemes (unmanaged DG, VPP, DR and microgrid), a dedicated, centralized control entity must be set up to implement corresponding control mechanisms, which is costly to operate in practice. The complexity of the business and operation models will significantly increase as more DERs are developed.

The current practice in the retail electricity market utilizes the net metering [2] mechanism to maximize the incentive for individual renewable generation providers, and is supported national wide in 39 states according to the Data Base of State Incentives for Renewables and Efficiency [27]. Any "net metering" programs that allow customers to receive payment for any excess generation produced by their solar panels are offered in the competitive market, where customers are free to choose a retail electricity provider (REP) [12] that provides the excess generation buy-back program that they like best. Although net metering brings the major step forward for the distributed solar markets in retail electricity market [14], the actual net metering policies (which include monetary values for solar production) are complicated and different from state-to-state and even by electric service territories within states. Take Texas as an extreme example, only parts of Texas are open to retail electric competition, such as Dallas and Houston, where companies that sell electricity to customers (retail electric providers, like Green Mountain Energy) are separate from the companies that manage the transmission and distribution of electricity. However, within this kind of competitive retail electricity market in Texas, only few retail electricity providers have the programs that offer value to those who generate excess solar power from their homes [28] like the Green Mountain Energy [29], where the one-month delay credits are applied to the eligible customers' outflow power from their renewable energy production. Individual renewable generation providers, especially homeowners with small-scale renewable generators, will face difficulty in having sufficient choices, such as not only selling their surplus renewable generation to few REPs.

To tackle the aforementioned technical difficulties, this thesis proposed a cloud-based framework to provide the customer-oriented Energy Management as a Service (EMaaS) for "*communities*", which are formed as virtual REPs by involved customers who own the DERs [30]. To be more specific, DERs owners can choose to join a service plan by agreeing to the benefits and rules in contract to EMaaS provider. Then they become customers of a certain community that is formed by other customers who also joined the same service plan. A new price appears when the community is formed and is utilized for customers trading their produced renewable energy to other customers within the same community. This trading among customers are denoted as the *"virtual trading"* throughout the thesis as it is performed virtually due to the physical power distribution

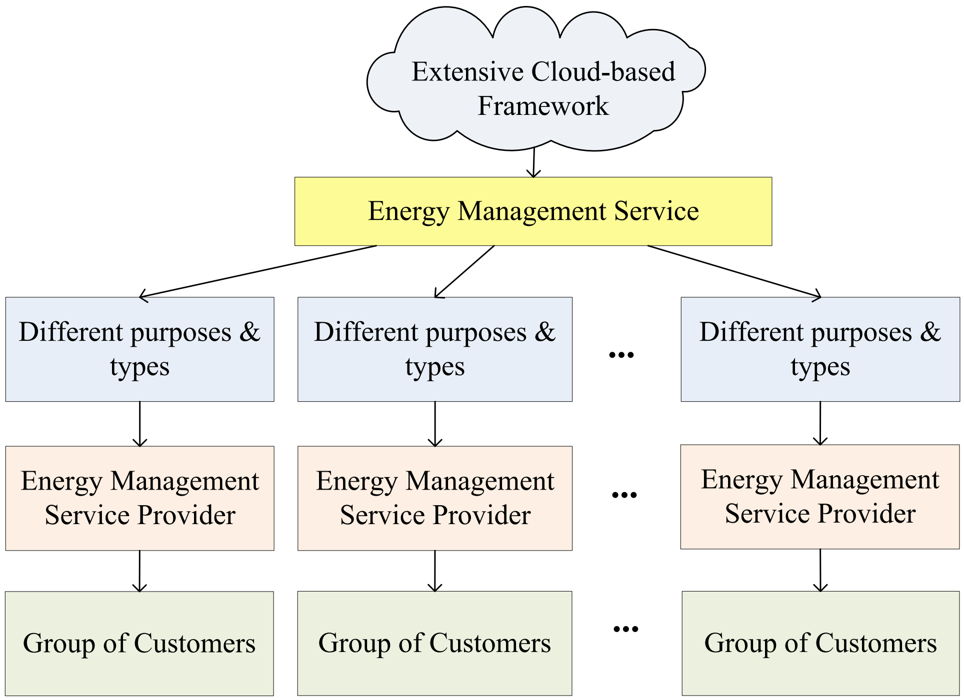

Figure 2.5: Concept of the cloud-based energy management service

lines may not exist among customers, and it can be realized efficiently via a mapping mechanism with the cloud-based framework. The virtual trading could be performed within the same community or across multiple communities (i.e., various EMaaS plans) as long as the agreements are made following the physically available line capacity from local utilities and the physical distribution network that supports both customers and non-customers of the energy management service. The paradigm of the proposed extensive cloud-based framework could support different purposes and types of services that are provided by multiple service providers to various groups of customers, as shown in Fig. 2.5. That is, the service could provide to customers who own various types of DERs (e.g., renewable energy resources or micro-turbine) to achieve different objectives (e.g., achieve the lowest electricity cost) by the corresponded service strategy developments. This thesis demonstrates a purpose that focuses on providing incentives to the group of prosumers who own the renewable DERs (i.e. the wind or solar), where the environment cost is considered along with the development of the energy management service strategy.

The discussed domain of this thesis lies on the scale of the retail electricity market. Information and the regulated prices from the wholesale electricity market are utilized like the existing REPs. The proposed cloud-based energy management can be easily adopted by existing retail electricity providers. The cloud-based energy management is provided as a service via an extensive framework. It can be viewed as a novel business model for REP providing the brand-new service plans to the heterogeneously located customers (i.e., customers could be physically located in the various power distribution line), and the supplements for REPs making the agreements to local utilities and the wholesale market. It significantly reduces infrastructure costs of decision making and increases the efficiency, reliability, and scalability.

The global cost (i.e., include electricity cost and the environment cost) can be minimized as the maximized incentives for each community via facilitating among the involved DERs, storage systems, and customers' behavior with the created plentiful choices (i.e., trading choices among other customers and between the entire power grid are discussed in chapter 3, the combined choices of trading and electricity usage in chapter 4) and further for the multiple communities via the cross-community interaction (discussed in chapter 5). The global cost for each community or for multiple communities is treated as the entire objective function in chapter 3, 4 and 5, and it includes another sub-level of incentive to the individual customer to maintain the proposed fairness in chapter 4. While performing the collaboration among various communities (which is served various service plans by various service providers) in the cross-community interaction, the virtual trading is performed at the community level instead of within the DERs owners while it is discussed for the single community. The traded amount of energy between communities has to be tracked since the benefit of the virtual trading depends on the amount of produced renewable energy within each community, thus, the traded amount between communities cannot exceed the corresponding community's original importing/exporting amount of energy from/to the main power grid, which is determined by the energy management within each community. In other words, the traded amount between communities in the cross-community interaction depends on the surplus or deficit amount of produced renewable energy within every community.

The proposed energy management service also supplements the planning of ancillary services as the valuable reference can be provided for designing the reserve capacity. EMaaS is able to enhance the renewable energy integration by determining and honoring commitments, which is similar to the unit commitment [31] but for DERs in distributed networks. Commitments would be designed and agreed between the EMaaS provider and local utilities as contracts, which already exist between REPs [12] and utilities. With the formed community, EMaaS is able to coordinate several DERs and demands as a single one, and is able to restrict and stabilize the amount of produced renewable energy according to the assigned upper bound and lower bound in each commitment as the constraints. The smaller the difference between the upper bound and the lower bound, the less capacity that conventional generators need to reserve. Therefore, the renewable generators within the green community would be able to work in a grid-friendly manner, with low spinning reserve requirement for conventional generations. More details of this part will be introduced in chapter 3. The commitments are also utilized to smooth the fluctuated penetration of EV loads and production capacities from DER within each community in chapter 4, where DERs and EVs within the same community can be operated grid-friendly, and help utilities managing their generators scheduling more efficiently.

Furthermore, the incomplete information is another major difference that distinguishes the proposed energy management in this thesis from energy management utilized in the wholesale electricity market. That is, the business model and the management are performed only depend on the heterogeneous involved DERs owners, who could be physically located in the various power distribution line. DERs owners could choose the different energy management service providers or different energy management service plans like the existing customer who can choose service plans from multiple REP. To meet the requirement of the customers' engagement with this characteristic of heterogeneous and dynamic, providing the energy management service via the extensive cloud-based framework can adopt the ability of dynamically serving various groups of DERs owners while acquiring the various pricing information and physical power networks' limitation from the wholesale electricity market or the local utility operators.

In the brief summary, the proposed work in this thesis is the novel business model and energy management service for prosumers in the retail electricity market scale. It provides incentives and the energy management to increase customers' participation, which is an essential factor for DR or DSM in smart grid, and smooths the fluctuation to operate DERs and EVs grid-friendly via the customers' behavior changes. It could successfully bridge the current practice in the retail electricity market to the future transformed electricity market structure and is the progressive approach to solve the difficult problem in smart grid, that is, how to attract customers to involve the management and use from renewable energy.

CHAPTER 3. EMAAS: CLOUD-BASED ENERGY MANAGEMENT SERVICE FOR DISTRIBUTED RENEWABLE ENERGY INTEGRATION

A paper published in IEEE Transaction on Smart Grid

Yu-Wen Chen, J. Morris Chang

3.1 Abstract

The increasing penetration of renewable energy has become a critical issue in recent years. The future power system is foreseen to depend on distributed energy resource (DER) excessively for continuous load support. Yet, DER providers are also facing limited choices in their produced renewable energy. Massive information and complicated cooperation emerging from involvers intensify issues in terms of efficiency, reliability and scalability. In this chapter, a cloud based framework is proposed to provide a customer-oriented Energy Management as a Service (EMaaS) for green communities, which are formed as virtual retail electricity providers (REPs) by involved DERs providers. It can be adopted by existing REPs or utilities. For each green community, the multi-period global cost is minimized to promote renewable energy, and renewable energy consumption is stabilized to enhance integration. A solvable linear programming model is formulated for EMaaS. The case studies results reveal the proposed EMaaS retains satisfactory performances.

3.2 Nomenclature

Parameters

G^b Production capacity of large-scale renewable generators.

G^s Production capacity of small-scale renewable generators.

D Electricity demand.

T^c Assigned capacity for power distribution line.

P^m Price for importing conventional energy.

P^s Price for exporting renewable energy to power grid.

P^r Price for trading renewable energy in green community.

T^u Upper bound for renewable energy integration.

T^l Lower bound for renewable energy integration.

C^s Corresponding cost for prosumers.

C^b Corresponding cost for large-scale renewable generators providers.

Variables

(i) Decision variables for small-scale renewable generators

I^d Import renewable energy for demand.

I^s Import renewable energy to storage.

I^m Import conventional energy for demand.

E^{rr} Export renewable energy to green community.

E^{rm} Export renewable energy to power grid.

E^{sr} Export stored renewable energy to green community.

E^{sm} Export stored renewable energy to power grid.

(ii) Decision variables for large-scale renewable generators

E^{bm} Export renewable energy to power grid.

E^{br} Export renewable energy to green community.

(iii) State variables for storage systems

S State of charge for storage.

Subscripts

i i_{th} small-scale renewable generator.

j j_{th} large-scale renewable generator.

t t_{th} time step.

z z_{th} power distribution line.

Sets

$\mathbb{N}$ For small-scale renewable generators.

$\mathbb{B}$ For large-scale renewable generators.

$\mathbb{T}$ For time step from 1 to K.

$\mathbb{Z}$ For power distribution lines.

$\mathbb{L}$ For customers connected to the same power distribution line.

3.3 Introduction

Greenhouse gases are believed to be a major cause for climate changes in temperature, storm severity, and sea level. Increasing the energy efficiency to reduce the greenhouse emissions from the combustion of fossil fuels becomes a critical goal for many countries, for example, the European Union has agreed to reduce greenhouse gases by 30% by 2020 [32]. Among different approaches, increasing the penetration of renewable energy in the country's electricity has been an important target for many states and countries. According to Renewable Portfolio Standard Program in California, the 2014 tracking progress report states the generation target as serving 33% of retail electricity from renewable resources by the end of 2020. Large-scale renewable generators (such as solar parks, wind farms) and distributed rooftop photovoltaic (PV) power can be adopted by companies and residents in order to achieve that goal. Proper management and trading strategies could maximize the incentives for renewable resource development and usage, and optimize operation costs and reduce carbon footprint for renewable generators.

However, integrating DERs can be challenging due to the fluctuations and uncertainties of uncontrollable and intermittent renewable energy resources [15][16]. Several potential challenges exist for renewable energy integration, including reserve capacity [17][18], scheduling, load management and forecasting [19].

In the literature, several approaches have been attempted to enhance renewable energy integration. Distributed generations (DG) and their integration attempts [20][21] have been investigated to dispatch bidirectional flows on aged distribution network designed for unidirectional flows. Due to the fact that conventional distribution management systems infrastructure commonly lack the capability of DG dispatching, power grids and local loads have to passively accept unmanaged DG outputs. In order to provide a managed renewable integration, a cluster of DG installations can be collectively bundled as a virtual power plant (VPP) [22] and operated by a centralized control entity.

As the core of VPP, the energy management systems (EMS) of a scheduling coordinator can maximize the cluster profit by managing its distributed energy resources (DERs) while considering their physical positions [23]. Demand response (DR) is also available as an energy management technique from demand-side perspective. As an important ingredient of smart grid, DR promotes both market efficiency and operational reliability, and is currently evolved in existing programs at different Independent System Operators (ISOs)/ Regional Transmission Organizations, such as California ISO (CAISO) and New York ISO [24]. Microgrid functions autonomously by incorporating localized DGs, storage systems, and controllable load. Microgrid control center optimizes operating states and coordinates components to pursue economic benefits in either grid-connected or standalone mode [25]. Multiple microgrids can participate in the market and effectively utilize the DERs through a two level multi-agent systems [26]. According to the above four renewable integration schemes (unmanaged DG, VPP, DR and microgrid), a dedicated, centralized control entity must be set up to implement corresponding control mechanisms, which is costly to operate in practice. The complexity of utilities' business and operation models will significantly increase as more DERs are developed.

Net metering [2] is an existing mechanism to maximize the incentive for individual renewable generation providers, and is supported national wide in 39 states according to the Data Base of State Incentives for Renewables and Efficiency [27]. Supported programs allow customers to receive payment for excess produced renewable energy in the competitive market, where customers are free to choose a retail provider that provides the excess generation buy-back program that they prefer. However, only few retail electricity providers (REPs) [12] offer buy-back programs, like Green Mountain Energy in Texas. Individual renewable generation providers, especially homeowners with small-scale renewable generators, will face difficulty in having sufficient choices, such as not only selling their surplus renewable generation to few REPs.

To tackle the aforementioned technical difficulties, this chapter proposed a cloud based framework to provide the customer-oriented Energy Management as a Service (EMaaS) for *green communities*, which are formed as virtual REPs by involved DERs providers. The proposed EMaaS could be adopted and operated by existing REPs or utilities. An intermediate service between utilities and customers is provided to promote the generation, trading and consumption of renewable energy. EMaaS actively facilitates among different components through a linear programming (LP) model to achieve two purposes for each green community: (i) maximizing the incentive (minimizing the global cost) to increase the willingness of both companies and residents to equip renewable energy generators and use the service, and (ii) enhancing renewable energy integration by determining and honoring commitments, which is similar to the unit commitment [31] but for DERs in distributed networks. Commitments would be designed and agreed between the EMaaS provider and local utilities as contracts, which already exist between REPs and utilities [12].

EMaaS is essentially a service provided on an extensive framework and also a business model for distributed renewable energy integration, that creates attempt to futuristic energy Internet [33]. When EMaaS helps the green communities to form as virtual REPs, a new price appears for customers trading produced renewable energy within the community. By trading with other customers within the same community following this price, customers can reduce their overall cost and benefit mutually while no dedicated physical controller or operating entity is required. With the option of trading within the green community and various components, customers have more options for their produced renewable energy. Finding the optimal global cost for each community becomes non-trivial due to the potential number of various combinations of options, especially when multi-period fluctuated prices, renewable generation forecasting, storage systems and electricity demand are considered together. To solve the problem efficiently, a linear programming (LP) model is formulated for EMaaS helping each community to achieve the optimal global cost by suggesting the ideal options for each customer's renewable generation.

The contributions of this chapter are summarized as follows. (i) To the best of our knowledge, this is the first work providing the customer-oriented energy management as a service (EMaaS) through a cloud based framework to achieve the multi-period global optimal costs for each green community, and promote renewable energy integration by determining and honoring commitments. The concept of forming green communities as virtual REPs by involved DERs providers allows customers to trade their produced renewable energy to each other, and be able to benefit mutually. Customers can have more trading options while the multi-period fluctuated prices, renewable generation forecasting, storage systems and electricity demand are considered altogether. (ii) EMaaS is a beneficial attempt for cloud application in power system community. It significantly reduces infrastructure costs of decision making and increases efficiency, reliability and scalability, based on the proposed virtual renewable energy trading system on the cloud. (iii) A linear programming model is formulated for EMaaS, and case studies are conducted to estimate and evaluate the performances of the proposed EMaaS.

The remainder of this chapter is organized as follows. Section 3.4 presents the system model, and section 3.5 gives the formulation model. Section 3.6 discusses the case studies, and the conclusion is summarized in section 3.7.

3.4 System Model

In this chapter, the four essential factors are the multi-period fluctuated prices, renewable generation forecasting, states of storage systems, and electricity demand. They are considered together by EMaaS so that the optimal global cost for each green community could be achieved. For example, if the fluctuated prices and the storage systems are the only considered factors, customers would store more renewable energy for future usage when the price is higher. However, they could store more renewable energy than their future demand, and degrade the service of others. Therefore, the electricity demand and the forecasted renewable generation must be considered together.

In the following subsections, first, a cloud computing based architecture is introduced, which represents the key enabler of EMaaS. Then, the framework with various components is secondly presented, and several utilized data are summarized. Since the physical power distribution lines may not exist between customers, the renewable energy trading scheme is performed virtually through a mapping in a cooperative procedure, which is addressed with an adjusting process in the last subsection.

3.4.1 Cloud Computing based Architecture

Cloud computing brings enormous advantages including avoiding capital investments, reducing maintenance expenses, providing secure managements, and simplifying implementations [34][35]. It is defined in National Institute of Standards and Technology [36] as the model for enabling ubiquitous, convenient, on-demand network access to a shared pool of configurable computing resources, which can be rapidly provisioned and released with minimal management effort or service provider interaction.

Providing the energy management service on the cloud infrastructure allows various components to access it easily through public or private cloud with thin client interfaces, such as web browser or application programming interface (API). Multiple green communities could be easily formed without any limitation, and the energy management is able to cope with the issues of efficiency, reliability and scalability even the complexity of coordinating the massive data is increased. Comparing to providing the service without the cloud infrastructure for serving M green communities, the cloud based framework could reduce the cost $M-1$ times, which includes the cost for establishing the local computational machine to execute the service, the duplicated implementation for the service and the maintenance. Existing major service models of cloud computing are Infrastructure

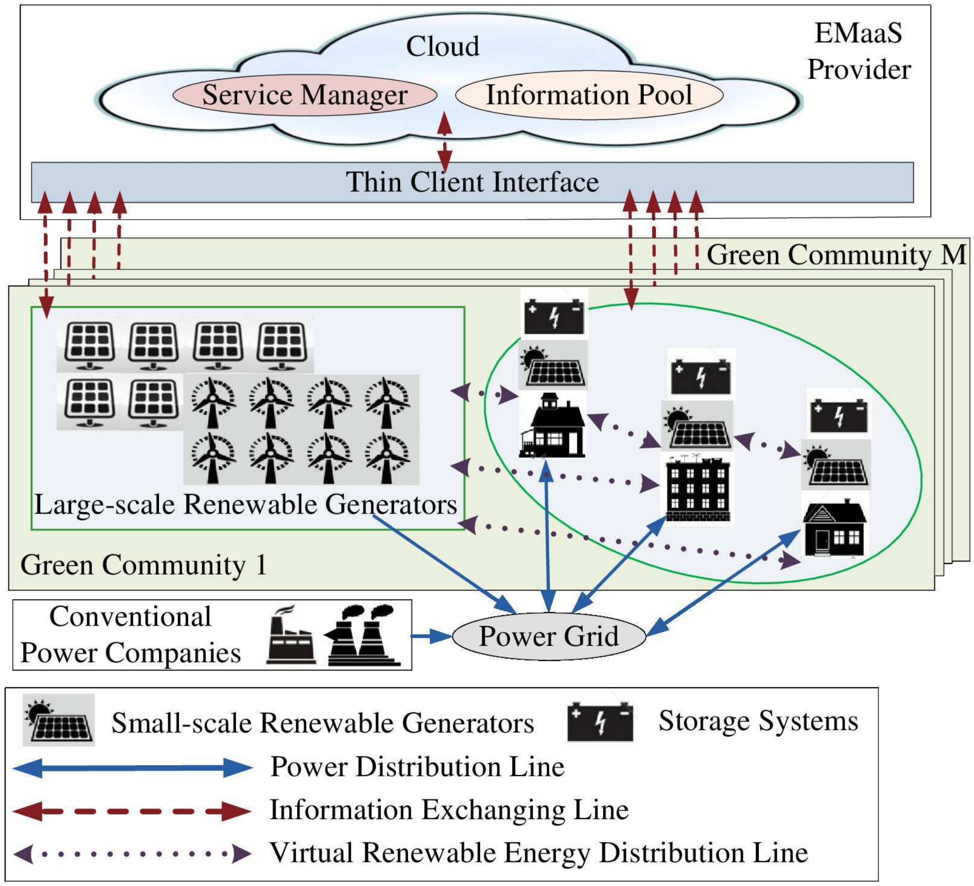

Figure 3.1: Framework

as a service (IaaS), platform as a service (PaaS) and software as a service (SaaS) [36]. The proposed Energy Management as a Service (EMaaS) is an extension of PaaS model and specifically designed for DERs providers forming virtual REPs to achieve optimal global costs and improve the renewable energy integration. It is applicable to large scale power system by including more involvers as customers.

3.4.2 Framework

The framework is presented in Fig. 3.1. An information pool and a service manager run on the cloud infrastructure. They are accessible to other components through the thin client interface via the information exchanging lines. Sequential time-series data depending on various geographic locations are stored in the information pool, and utilized by the service manager. The service manager provides EMaaS for multiple green communities and suggests ideal choices to every customer within the green community.

The green community is formed by two types of non-dispatchable DERs providers. The first type DER is large-scale renewable generators, which are built by individual companies with the purpose of raising revenue, such as wind farms and solar parks. The second type DER is small-scale renewable generators, e.g. PV panels equipped on the rooftop of various types of buildings. These small-scale renewable generators providers are called *prosumers*, since they are both the energy producer and the energy consumer. Reducing the electricity cost for daily demands is their priority. Both large-scale and small-scale renewable generators connect to a power gird following the signed interconnection agreements with their local electric transmission and distribution utility, such as the electric substantive rule 25.211 addressed in public utility commission of Texas [37]. The power grid is also supported by the conventional power companies (GENCOs) with various conventional generators, like fossil fueled generators. They are capable of providing sufficient energy to the loads in power grid but are not environment-friendly.

Storage system is another essential component for the proposed framework structure. It is assumed to be efficient and able to store and release energy quickly, such as super-capacitors. The storage system is maintained by the service manager, and cooperates with renewable energy generators. Individual storage and distributed renewable resource are connected in pairs at same location to a set of DERs, and are only able to charge from the renewable energy produced by renewable generators while operating in the proposed EMaaS. The maximum storage capacity is assigned as S^{max} for each individual storage.

3.4.3 Utilized Data

EMaaS utilizes the sequential time-series data gathered from different components, which includes the parameters of $\{G^b$, G^s, D, T^c, P^m, P^r and $P^s\}$ for K time steps ahead. G^b and G^s are the production capacities of renewable generators. They can be forecasted according to the local weather report with other environment conditions, such as the different angles, available spaces or positions for each renewable generator[38][39]. D is the electricity demand that could be predicted by historical data, or entered directly from customers in advance. T^c is the assigned capacity for each power distribution line. It is decided by local power utilities and depends on the physical distribution network, including the supported loads from both non-EMaaS and EMaaS customers.

$\{P^m, P^r, P^s\}$ are three price indicators used by EMaaS to calculate the corresponding costs for satisfying customers' electricity demands. P^m indicates the price of importing power from conventional power grid. It is time-variant and is provided to EMaaS as a fixed known input value for each time step by conventional power companies or local utilities based on their predictions. Environment concern is included in the price indicators. P^s is viewed as a lower price than P^m since it excludes environment costs, such as CO_2 emission. The relationship between P^s and P^m is showed in (3.1), where α depends on various environment penalties in each region. P^r appears when the green community is formed as a virtual retail electricity provider. It is presented in (3.2) as a value between P^m and P^s, where β is assigned by the contract according to the agreement between customers and EMaaS provider. It is similar to the electricity price sold to customer by existing REPs.

$$P^s = \alpha P^m, \qquad 0 < \alpha < 1 \tag{3.1}$$

$$P^r = \beta(1-\alpha)P^m + P^s, \qquad 0 < \beta < 1 \tag{3.2}$$

3.4.4 Cooperative Procedure

A practical cooperative procedure shown in Fig. 3.2 is proposed for the service manager interacting with other components. In the beginning of the procedure, the service manager gathers K time steps ahead utilized data from information pool and other components. Then the energy management is run for each green community to achieve the optimal global benefits and determine each decision variable. Corresponding

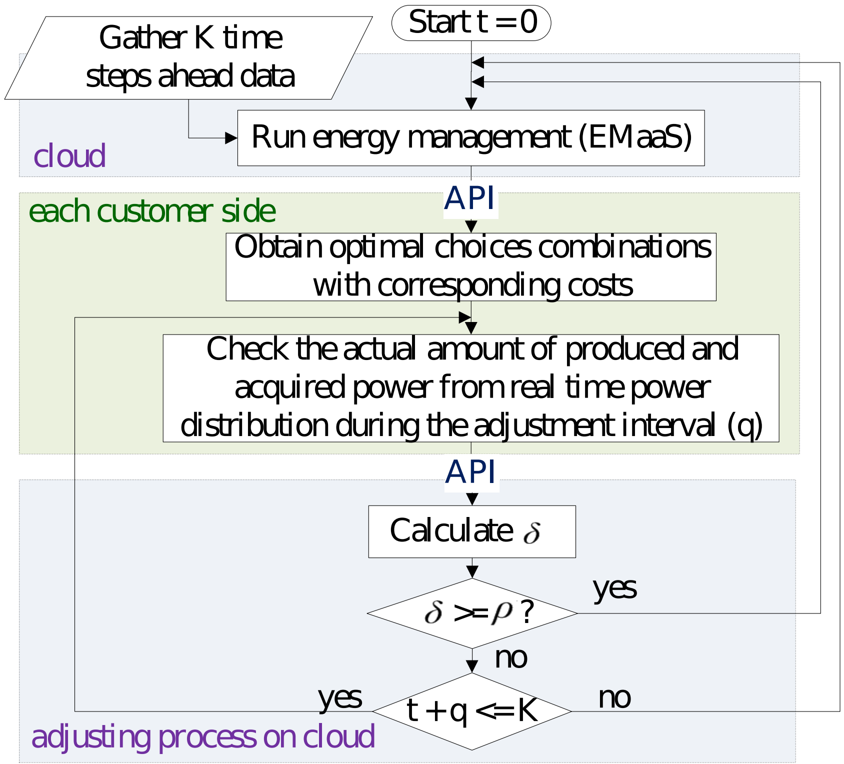

Figure 3.2: Cooperative procedure

cost for each customer is calculated based on various combinations of decision variables and is recorded as the billing reference. Suggested amount of imported/exported power for each time step in K are provided by the service manager to renewable resource providers as their ideal demands. Suggestions are sent through APIs, which are presented as the dashed information exchanging lines in Fig. 3.1. Large-scale renewable generators will export the total produced power, and $A^d_{i,t}$ in (3.3) is mapped as the amount for each prosumer to import/export while it is positive/negative. $A^s_{i,t}$ in (3.4) is indicated to prosumers as the amount of charging or discharging their storage system.

$$A^d_{i,t} = I^d_{i,t} + I^s_{i,t} + I^m_{i,t} - E^{rr}_{i,t} - E^{sr}_{i,t} - E^{sm}_{i,t} - E^{rm}_{i,t} \tag{3.3}$$

$$A^s_{i,t} = I^s_{i,t} - E^{sr}_{i,t} - E^{sm}_{i,t} \tag{3.4}$$

The service is not practical if the suggested ideal demands cannot be satisfied due to other physical power distribution network constraints or the inaccurate gathered data caused by forecast error, such as unpredicted sudden changes in electricity demands. Therefore, an adjusting process is required to complete the cooperative procedure. When unexpected situations or forecast errors are observed, the insufficient or surplus amount (ε^a) of energy will import from the external power grid with the current price P^* or export to the external power grid with the price αP^*, and cause a differential cost (ε^c). The difference between P^* and the utilized P^m would also be treated as forecast error and affects ε^c.

An adjustment interval is used as q minutes in the adjusting process. It can be assigned by following the current operation in real time market, where CAISO uses 5 minutes in real-time economic dispatch process [40]. During each adjustment interval, customers check their actual amount of produced and acquired power, which is operated and distributed in parallel by local electric distribution utilities in real time through the solid physical distribution lines in Fig.3.1. Service manager obtains these real time data from customers through APIs, and records a factor (δ) as the ratio of the differential cost (ε^c) to the total corresponding costs (C^{opt}) for the entire green community. If δ is larger than a threshold (ρ), the service manager will re-trigger the energy management for the next K time steps period. Otherwise, the determined decision variables will be followed by each customer continuously in the next adjustment interval. When the time $(K - q)$ is reached, the energy management will be re-triggered for the succeeding K time steps.

3.5 Formulation for EMaaS

The proposed EMaaS cooperates with various components to achieve two purposes for each green community: maximizing the incentive as minimizing the global cost and enhancing renewable energy integration. A linear programming model is formulated for EMaaS and limited to individual green community with massive information and involvers. Operation costs for storage systems and renewable generations are assumed to be negligible. The model is formed by decision variables $\{I^d, I^s, I^m, E^{rr}, E^{rm}, E^{sr}, E^{sm}, E^{bm}, E^{br}\}$ and a state variable $\{S\}$.

The objective function for the model is to maximize the benefits as minimizing the global corresponding cost for every prosumer (C^s) and large-scale renewable generator provider (C^b) in the entire green community during K time steps period. It is shown in (3.5), where prosumers tend to minimize their electricity cost in (3.6), and large-scale renewable generators providers are trying to maximize their revenues in (3.7).

$$min \sum_{t \in \mathbb{T}} C_t^{opt} = \sum_{t \in \mathbb{T}} (\sum_{i \in \mathbb{N}} C_{i,t}^s + \sum_{j \in \mathbb{B}} C_{j,t}^b) \tag{3.5}$$

$$\begin{aligned} C_{i,t}^s = \quad & I_{i,t}^m \times P_t^m - (E_{i,t}^{sm} + E_{i,t}^{rm}) \times P_t^s \\ & + \left(I_{i,t}^d + I_{i,t}^s - E_{i,t}^{sr} - E_{i,t}^{rr}\right) \times P_t^r \end{aligned} \tag{3.6}$$

$$C_{j,t}^b = E_{j,t}^{bm} \times (-P_t^s) + E_{j,t}^{br} \times (-P_t^r) \tag{3.7}$$

The following constraints subject to the objective function in the formulated model to ensure the limitation of power system or physical equipments will not be conflicted, and the ability of renewable energy integration could be achieved. Constraint (3.8) shows the basic criterion to attract customers to the energy management, which is providing the guaranty to satisfy the requested electricity demand for prosumers regardless of other load management algorithms.

$$D_{i,t} = I_{i,t}^d + I_{i,t}^m \tag{3.8}$$

For each time step, the summation of the suggested demands for customers connected to the same power distribution line needs to satisfy the assigned capacity for corresponding power distribution line. It is shown in constraint (3.9), where $A_{i,t}^d$ is addressed in (3.3).

$$\sum_{i \in \mathbb{L}_z} A_{i,t}^d + \sum_{j \in \mathbb{L}_z} (E_{j,t}^{bm} + E_{j,t}^{br}) \le T_{z,t}^c \qquad \forall z \in \mathbb{Z} \tag{3.9}$$

For the renewable generation, constraint (3.10) and (3.11) assure that the exported energy is equal to the produced amount. Since the total available renewable energy in the green community at each time step depends on different choices of other prosumers, it also needs to be traced with (3.12) to avoid the imported amount exceeding the available amount.

$$E^{br}_{j,t} + E^{bm}_{j,t} = G^{b}_{j,t} \tag{3.10}$$

$$E^{rr}_{i,t} + E^{rm}_{i,t} = G^{s}_{i,t} \tag{3.11}$$

$$\sum_{j \in \mathbb{B}} E^{br}_{j,t} + \sum_{i \in \mathbb{N}} \left(E^{sr}_{i,t} + E^{rr}_{i,t}\right) = \sum_{i \in \mathbb{N}} \left(I^{d}_{i,t} + I^{s}_{i,t}\right) \tag{3.12}$$

The storage is assumed to be efficient so the energy conversion loss can be ignored, and the operational range for state of charge is set from 0 to S^{max}. The state variable, S, depends on the state variable in the previous time step and the charging or discharging decision in current stage, and their relation is indicated in (3.13). Constraint (3.14) guarantees the exported energy from the storage will not exceed the current existing amount in storage, and constraint (3.15) promises that storage will not be saturated after importing energy from renewable generators.

$$S_{i,t+1} = S_{i,t} - \left(E^{sm}_{i,t} + E^{sr}_{i,t}\right) + I^{s}_{i,t} \tag{3.13}$$

$$S_{i,t} - \left(E^{sm}_{i,t} + E^{sr}_{i,t}\right) \geq 0 \tag{3.14}$$

$$S_{i,t} + I^{s}_{i,t} \leq S^{max}_{i} \tag{3.15}$$

T^u and T^l are two values used for enhancing renewable energy integration. They are assigned as the upper bound and lower bound according to various commitments. Since the formed green community allows EMaaS to coordinate several DERs and demands as a single one, it is able to restrict and stabilize the amount of produced renewable energy in between these two values. The smaller the absolute value of T^u minus T^l is, the less capacity that conventional generators need to reserve. Therefore, the renewable generators within the green community would be able to work in a grid-friendly manner, with low spinning reserve requirement for conventional generations. Constraint (3.16) presents the amount of total requested electricity demand minus the total imported energy from the conventional generators for each time step. This indicates the amount of renewable energy production for the green community at each time step.

$$T^l \leq D_{total} - \left[\sum_{i \in \mathbb{N}} \left(I_{i,t}^m - E_{i,t}^{sm} \right) - \sum_{j \in \mathbb{B}} E_{j,t}^{bm} \right] \leq T^u \tag{3.16}$$

The formulated optimization problem is solvable by state-of-the-art commercial or open-source LP solvers, with the objective function in (3.5). It is subjected to various constraints from (3.8) to (3.16), and all variables are greater or equal to 0.

3.6 Case Studies

This section presents case studies with various numbers of EMaaS customers, two scenarios with different ratios of renewable energy production to the electricity demand, and three commitment cases. Cost savings performance, renewable energy integration performance, effects of storage systems, and computational performance are discussed in detail.

3.6.1 Test Cases

The time horizon K for EMaaS is set to 24 by following the current existing day-ahead operation interval provided by CAISO, and each time step represents an hour. Fig. 3.3, Fig. 3.4 and Fig. 3.5 illustrate the utilized data in our case studies. Only one large-scale renewable resource is assumed to exist in the green community, and its productivity is generated in a uniform distribution with the range from 30 kW to 170 kW. Several DERs exist in the community as well, and their productions follow the basis in Fig. 3.3. This basis is designed according to the database from CAISO, where PV based renewable generations are able to work from clock of 6 to 20 a day during

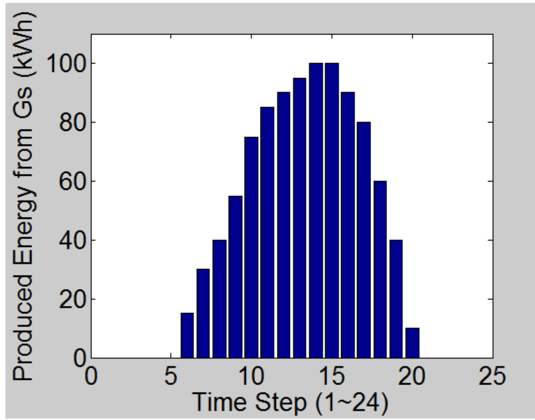

Figure 3.3: Basis for the production of G^s

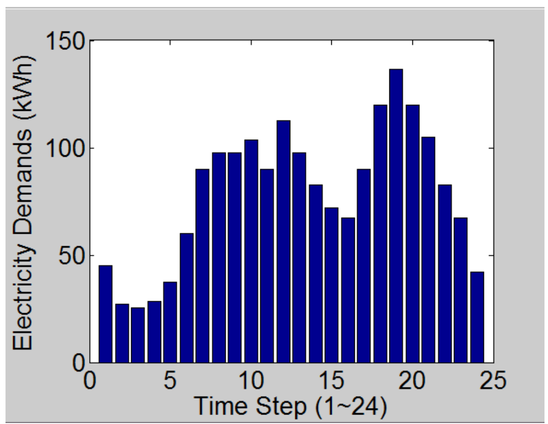

Figure 3.4: Electricity demands basis

the summer time. Each PV generator has various coefficients, like different sizes and positions. Thus, G^s is calculated as the basis multiplied by a uniform distribution in the case studies.

The electricity demand basis is based on the typical household load profile showed in Fig. 3.4. With different preferences that depend on the environment or habits of each household, the requested electricity demands for each prosumer are generated by multiplying the basis to a uniform distribution with the range from 0.5 to 1.5. Customers are randomly connect to different distribution lines, and the available capacities (T^c) for each line are assigned as the number of connected customers times 115 kWh, which is smaller than the maximum in electricity demand basis.

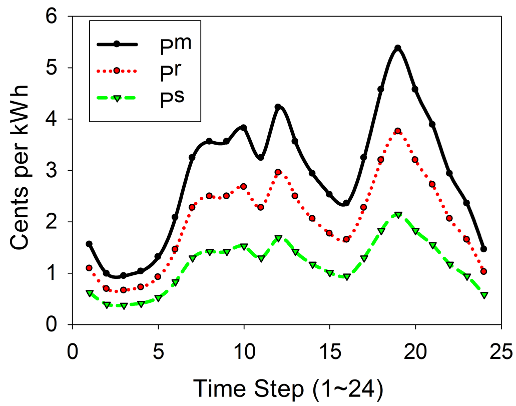

Figure 3.5: Price Indicators

To bring the reality into the case studies, the price indicator P^m is treated as a quadratic fuel cost function in (3.17), which is widely used by thermal power plants [41]. We assume there is a conventional generator supporting 3600 residents, including both non-EMaaS and EMaaS customers. It is able to produce enough power (P_{out}) to support the total electricity demands under its output capacity constraints, which is 500 MW for the maximum and 100 MW for the minimum as the data provided in [41]. With the cost function coefficients $(a, b, c) = (240, 7, 0.007)$, P^m is set between 1 to 6 cents per kWh. The α and β used for P^s and P^r are set as 0.4 and 0.5. The values of the price indicators are shown Fig. 3.5. The maximal storage capacities are all set as equals to 30 kWh.

$$Cost(P_{out}) = a + b(P_{out}) + c(P_{out})^2 \tag{3.17}$$

The ratio of renewable energy production to the electricity demand is the critical factor for virtually trading renewable energy within the green community, and can be expressed in terms of $(\sum G^s + \sum G^b)/D$. With a higher ratio, more available renewable energy could be traded to achieve a lower global cost for each green community. To present the effects from different ratios of produced renewable energy to the electricity demand, two scenarios in Table 3.1 are used in the case studies. The ratio is calculated in percentage as 35.8% to present the low ratio case in scenario 1, and as 66% to indicate

Table 3.1: Scenario Settings for Case Studies

Scenario	Uniform Distribution Range for G^s	$(\sum G^s + \sum G^b)/D$
1	$0.2 \sim 1.2$	35.8%
2	$0.8 \sim 1.8$	66%

the high ratio case in scenario 2. For both scenarios, the renewable energy production capacities comply interconnection agreements.

3.6.2 Energy Management Schemes

Two management schemes with different strategies are used to compare with the proposed EMaaS. The first scheme is without green community and is multi-time steps based (MT). It is widely used in unmanaged DGs [20]. Customers make their decisions based on the fluctuated price indicators individually. They tend to store the produced renewable energy when P^s is low, and use it when P^m is high. Thus, the cost under multi-time steps could be reduced.

The second scheme is a single time step version of EMaaS (ST-C), i.e. customers in the green community are organized in a cooperative pattern. This scheme is following the idea from P. Bazan [42]. In the ST-C approach, at each time step, customers tend to satisfy their electricity demands first by using available generations and local storage systems. The unsatisfied demands will be supplied by purchasing the available renewable energy from the community with price P^r, or from the conventional power grid with price P^m. After the demands are satisfied, customer will store the surplus produced renewable energy to his local storage system for his future demands with zero cost. When the storage system is saturated, the surplus renewable energy will be traded to other customers within the green community with price P^r, and to the main power grid with the price P^s.

Three energy management schemes, including the approach of MT, ST-C and the proposed EMaaS, are based on LP problems. CPLEX 12.5 [43] was employed as the LP

Table 3.2: Cost savings performance

	Scenario 1						Scenario 2					
	Cost (hundred dollar)			Cost ratio to EMaaS			Cost (hundred dollar)			Cost ratio to EMaaS		
Customer Size	MT	ST-C	EMaaS	MT	ST-C	EMaaS	MT	ST-C	EMaaS	MT	ST-C	EMaaS
500	205.03	205.15	197.4	1.0386	1.0392	1	149.69	148.74	112.49	1.3307	1.3223	1
1000	407.54	407.12	392.02	1.0395	1.0385	1	303.47	301.38	231.15	1.3129	1.3038	1
1500	610.91	610.98	588.38	1.0382	1.0384	1	453.73	450.91	345.09	1.3148	1.3066	1
2000	818.61	818.14	788.1	1.0387	1.0381	1	605.59	600.84	461.11	1.3133	1.3030	1
2500	1021.89	1021.6	984.12	1.0384	1.0381	1	754.29	750.98	574.13	1.3138	1.3080	1
3000	1223.37	1223.68	1178.66	1.0379	1.0382	1	910.64	906.54	692.91	1.3142	1.3083	1

solver in the case studies. In the following subsections, different performance indices are investigated for the proposed EMaaS. In the performance of cost savings and storage system, T^u and T^l are set to be the values (extremely large T^u and extremely small T^l) that did not provide the actual bounding in the commitments.

3.6.3 Cost Savings Performance

With different numbers of customers under two scenarios, Table 3.2 lists the absolute cost values for three energy management schemes and the cost ratios to EMaaS. In scenario 1, the cost for MT scheme requires 3.86% more than EMaaS, and ST-C scheme requires 3.84% more. When the ratio of produced renewable energy to the electricity demand is increased in scenario 2, more renewable energy is able to be traded within the green community so the cost can be significantly reduced by the proposed EMaaS. The cost for MT scheme would be 31.7% more than EMaaS, and ST-C scheme requires 30.9% more. The achievable profits remain stable while the number of customers increases, and are significant when the ratio of produced renewable energy to the electricity demand is higher. It is promising since increasing renewable energy production capacity is expectable in many states, like California. The proposed EMaaS is able to maximize the incentive for individual companies or residents equipping renewable energy generators and using the service.

Table 3.3: Commitment Cases Under Scenario 1

	EMaaS-case1	EMaaS-case2	EMaaS-case3
T^u	33000 kWh	32000 kWh	31000 kWh
T^l	0 kWh	0 kWh	0 kWh

3.6.4 Renewable Energy Integration Performance

To demonstrate the capability of the bounds used in the commitment for renewable energy integration, three cases are presented in Table 3.3 with the customer size of 500 under scenario 1. Table 3.4 presents the renewable energy production from the green community with different energy management schemes. As expected, when T^u is set to be a lower value, EMaaS is able to reduce the difference between the highest and the lowest production from the green community. Therefore, conventional generators could decrease the reserve capacity more, and enhance the ability of integrating renewable generators with conventional generators. However, as the value of T^u decreases, the cost will increase as shown in Fig. 3.6. A trade-off exists between the cost and the integration ability. Such reference provides valuable information for EMaaS provider and local utilities to determine suitable bounds for commitments in the contract.

3.6.5 Effects of Storage Systems

Fig. 3.7 shows the comparison of cost ratio to the case of EMaaS with storage system under scenario 2 (in Table 3.1) to discuss the impact of the storage systems. While the storage systems are not involved in the energy management, the cost for EMaaS is 7.65% more, and yet 20.3% less than the scheme of ST-C. This illustrates that the proposed EMaaS is able to reduce the cost for green communities regardless of the storage systems, and the storage systems can further enhance the capability of EMaaS. The comparison between the scheme of ST-C regardless of storage systems also indicates that the advantages of storage systems can only be guaranteed when the multi-period

Table 3.4: Renewable Energy Integration Performance

	Renewable energy production from the green community (kWh)			
t (hr)	ST-C	EMaaS-case1	EMaaS-case2	EMaaS-case3
1	136.5481	25.88131	25.88131	25.88131
2	151.5569	0.075705	0.075705	0.075705
3	179.5985	0.01585	0.01585	0.01585
4	77.50117	0	0	0
5	155.5623	0	0	0
6	5308.069	0	0	0
7	10862.52	1845.367	1845.367	1845.367
8	14343.48	23853.5	14343.5	14343.5
9	19466.67	18620.8	29130.8	30130.8
10	26664.03	33000	32000	31000
11	29329.46	27130.57	28130.57	29130.57
12	30801.27	**33000**	**32000**	**31000**
13	33574.5	**33000**	**32000**	**31000**
14	35050.92	**33000**	**32000**	**31000**
15	**35449.82**	**33000**	**32000**	**31000**
16	31295.11	21370.3	24370.3	27370.3
17	28420.09	28419.98	28419.98	28419.98
18	21495.68	21495.73	21495.73	21495.73
19	13987.43	28987.55	28987.55	28987.55
20	3630.235	3630.319	3630.319	3630.319
21	84.25047	84.29267	84.29267	84.29267
22	198.323	198.2815	198.2815	198.2815
23	101.1395	101.1212	101.1212	101.1212
24	46.20506	46.24026	46.24026	46.24026

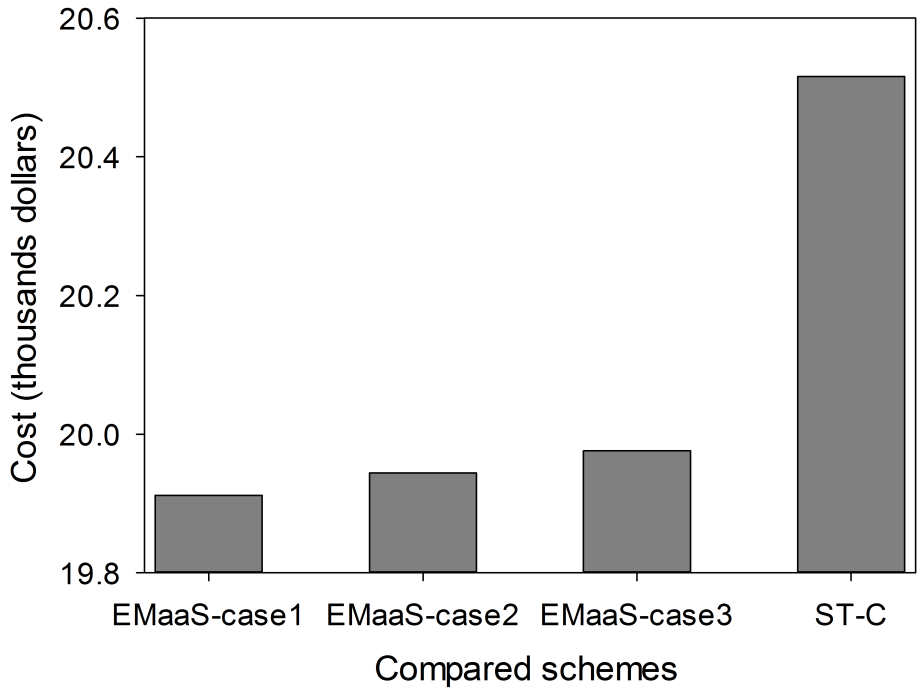

Figure 3.6: Costs with various commitment cases

information is considered altogether. Without considering the information in future time step, customers will miss the opportunity to lower their costs by selling the surplus renewable energy with higher P^r or P^s at the current time step and purchasing with lower price P^m or P^r in the future time step.

3.6.6 Computational Performance

The computation time for cloud based service can be divided into two parts. The first part is for executing the service, and the second part is for the cloud managing the data, which includes the connection time from each component. The second part is relatively small, and several works have been proposed to improve the communication delays to enable real-time operation for the cloud application [34]. This chapter proposes the energy management as a service through the cloud based framework. The computation performance is focusing on the first part of the computation time for executing the service

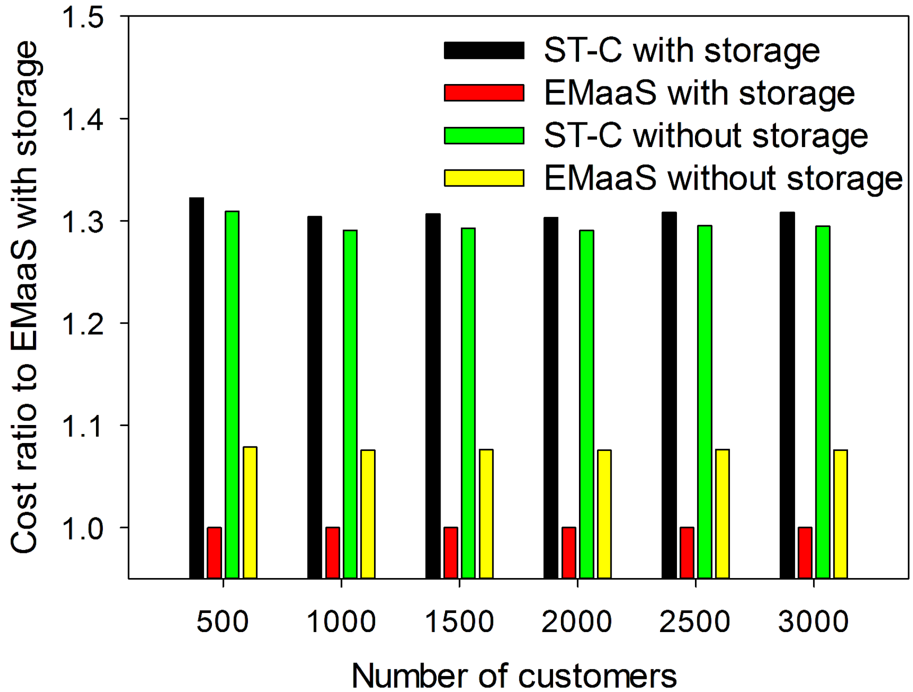

Figure 3.7: Cost ratio to EMaaS with storage system

to find optimal suggestions. The execution time of the service depends on different instance types provided by the existing cloud computing platform. To estimate the computation time in modern cloud computing platform, a publicly accessible Linux server equipped with 32 cores and 126 GB memory under medium load is used in case studies. The scale of resources of this server is comparable to most provided instances from Amazon Elastic Compute Cloud [44].

The proposed EMaaS is formulated as a linear programming problem, which is efficiently solvable in polynomial time [45]. Fig. 6 shows the exact computation time for the number of customers from 1000 to 15000, where 15000 can be considered as a large enough amount to present as a massive community. This further demonstrates the proposed EMaaS is realistic and handles the day ahead operation and the adjustment interval very well. The computation time for the size of 1000 is only 7 seconds, and 3.2 minutes for the size of 15000. It is significantly smaller than the day-ahead operation interval (24 hours), and is sufficient for the adjustment interval in the adjusting process (5 minutes from the CAISO real-time economic dispatch process). Therefore, the energy management is manageable and practical to overcome unexpected situations.

3.7 Conclusion

In this chapter, a cloud based framework is proposed to provide the customer-oriented Energy Management as a Service (EMaaS) for green communities, which are formed as virtual retail electricity providers (REPs) by involved distributed energy resources (DER) providers. EMaaS facilitates comprehensively among different types of generators, storage systems, and utilizes sequential time series data. Furthermore, EMaaS could be adopted and operated economically by existing REPs or utilities, and is practical with the cooperative procedure. With the formulated linear optimization model, EMaaS is shown to be practical and manageable from the estimated computational time on a high-end publicly accessible server. Two advantages for EMaaS are as followed:

(i) *Achieving the multi-period global optimal cost.* Electricity price and environment concern are considered together in the cost, and calculated based on various combination of decision variables, which are suggested for individual customers through a linear programming model. The global optimal benefit as minimizing corresponding cost for each green community during the K time steps can be achieved. EMaaS is able to increase the willingness of both companies and residents to equip renewable energy generators and use the service.

(ii) *Enhancing renewable energy integration.* The strategy in EMaaS successfully promotes renewable energy integration by reducing the reserve capacity for the dispatchable conventional generators and honoring commitments for the green community. The existing trade-off between minimizing the corresponding cost and enhancing the capability of renewable energy integration is shown clearly in the case studies. Such reference provides valuable information for EMaaS provider and local utilities to determine suitable bounds for commitments in the contract.

ACKNOWLEDGMENTS

The authors would like to thank Dr. Guangchao Geng from Zhejiang University for the fruitful discussions of this chapter.

CHAPTER 4. FAIR DEMAND RESPONSE WITH ELECTRIC VEHICLES FOR THE CLOUD-BASED ENERGY MANAGEMENT SERVICE

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4.1 Abstract

Fluctuated penetration of electric vehicle (EV) loads and production capacities from distributed energy resource (DER) bring large impacts to power systems. To smooth fluctuations, financial incentives have to be maximized for customers controlling their consumption patterns. A fair demand response with electric vehicles (F-DREV) is proposed for the cloud based energy management service. Customers with EV, DER, storage and multiple loads form communities and obtain optimal choices (electricity usage and trading) from F-DREV. F-DREV aims to maximize incentives by minimizing global cost for each community within the given time period, and smooth fluctuations. In order to attract customers to actively participate, we propose the fairness as "customers with higher participation level can reduce their individual cost more than those with lower participation level within the same community", which is attainable by customizing trading prices. A binary linear programming model is formulated, and performances are evaluated in experiments.

4.2 Nomenclature

Parameters:

G DER production capacity.

T^c Assigned capacity for power distribution line.

P^b Price for buying energy from power grid to community.

P^s Price for selling produced renewable energy from community to power grid.

P^u Highest trading price within community.

P^l Lowest trading price within community.

P^{rb} Customized buying price within community.

P^{rs} Customized selling price within community.

P^e Price for exporting energy from EV.

D Summation of the requested fix loads.

R Required operating time for deferrable load.

α Starting time for deferrable loads and EV.

β Ending time for deferrable loads and EV.

γ Power consumption rate for EV.

ηc Charging efficiency for storage and EV.

ηd Discharging efficiency for storage and EV.

EV^{init} Initial capacity of EV when arriving.

EV^{end} Required capacity of EV when leaving.

T^u Upper bound for smoothing the fluctuation.

T^l Lower bound for smoothing the fluctuation.

w Weight for different load types.

Subscripts:

i i_{th} customer.

j j_{th} interruptible or non-interruptible load.

t t_{th} time step.

z z_{th} power distribution line.

Superscripts:

r Distributed energy resource (DER)

m Power grid

c Community

e Electric vehicle (EV)

s Storage

d Load usage

fl Fixed load

il Interruptible load

nl Non-interruptible load

Sets:

$\mathbb{N}$ For customer from 1 to N.

$\mathbb{T}$ For time step from 1 to K.

$\mathbb{Z}$ For power distribution lines.

$\mathbb{L}$ For customers connected to the same power distribution line.

$\mathbb{IL}$ For interruptible loads.

$\mathbb{NL}$ For non-interruptible loads.

Choice variables for DER:

E^{rc} Export produced energy from DER to community.

E^{rm} Export produced energy from DER to power grid.

E^{re} Export produced energy from DER to EV.

E^{rs} Export produced energy from DER to storage.

E^{rd} Export produced energy from DER for load usage.

Choice variables for storage:

I^{ms} Import energy from power grid to storage.

I^{cs} Import energy from community to storage.

I^{rs} Import energy from DER to storage.

I^{es} Import energy from EV to storage.

E^{sm} Export energy from storage to power grid.

E^{sc} Export energy from storage to community.

E^{se} Export energy from storage to EV.

E^{sd} Export energy from storage for load usage.

S State of charge for storage.

Choice variables for EV:

I^{me} Import energy from power grid to EV.

I^{ce} Import energy from community to EV.

I^{re} Import energy from DER to EV.

I^{se} Import energy from storage to EV.

E^{em} Export energy from EV to power grid.

E^{ec} Export energy from EV to community.

E^{es} Export energy from EV to storage.

E^{ed} Export energy from EV for load usage.

S^{e} State of charge for EV.

Choice variables for loads:

I^{md} Use the energy from power grid.

I^{cd} Use the energy from community grid.

I^{rd} Use the energy from DER.

I^{sd} Use the energy from storage.

I^{ed} Use the energy from EV.

Binary control variables: $\{O^{il}, O^{nl}, O^{a}\}$

4.3 Introduction

In recent years, electric vehicle (EV) and distributed energy resource (DER) have been dramatically increased and popularized, due to their effectiveness in reducing greenhouse emissions and making power grid environment-friendly. The expected fluctuated penetration of EV loads and production capacities from DER bring large impacts to the power system not only as additional positive and negative loads, but also on reserving capacity [46]. Impacts of these fluctuated loads become more significant without proper management when technology such as Vehicle-to-Grid (V2G) enables EVs to work as the grid resources by providing power back to the power grid [47]. In order to smooth the fluctuation of EVs and DERs to allow them operate grid-friendly, it is critical to provide financial incentives for customers controlling their consumption patterns and their EV charging schedules. Providing the financial incentives is the focus of this chapter.

Literatures of demand response and EV charging scheduling have provided financial incentives as *"electricity usage choices"*, which allow customers to utilize DERs, controllable loads and storages to change demands in response to the fluctuated electricity prices over time. Residential electricity costs are minimized with the cooperation of various types of loads through the home energy management system in [48], and smart home controller in [49]. An optimization algorithm in the residential level is proposed in [50]. Authors in [51] and [52] propose the demand response schemes to minimize the global cost through a formulated game. Paper [53] deals with load control in multiple residences. Scheduling managements are discussed in virtual power plant [23] for DERs with storage to maximize profits, and in EV aggregator [46] to absorb the EVs penetration while minimizing costs for aggregator. To accommodate EV charging while keeping the peak demand unchanged, [54] proposes an incentive based demand response strategy with critical and controllable loads. However, unlike the cloud based framework, difficulty exists in above literatures due to the requirement of duplicated, dedicated control entity and corresponding control mechanisms. Moreover, none of them consider the *"trading choices"* among customers, which can boost the incentives for customers.

Trading choices appear when customers become owners of grid resources, such as EV with V2G and DER. They are utilized in net metering mechanism as incentive by retail electricity providers (REP) [12], but only few buy-back programs are offered and are not available among customers. Our previous work [30] proposes a cloud based framework to provide customer-oriented Energy Management as a Service (EMaaS) for *"community"*, which are formed as virtual REPs by involved DERs providers. A new price appears when the community is formed, and is utilized for customers performing the *"virtual trading"* for their produced renewable energy within the community to benefit mutually. The trading is performed virtually due to the physical power distribution lines may not exist among customers, and can be realized efficiently via a mapping mechanism with the cloud based framework. The cloud based energy management is provided as a service via an extensive framework and is also a business model for distributed renewable integration. It significantly reduces infrastructure costs and increases efficiency, reliability and scalability. But still, how to utilize it for demand response and EV charging scheduling to adjust electricity usage for customers within community is an unexplored area.

Furthermore, to substantially attract individual customer, allowing customers form the community to trade mutually with the same new formed price might not be enough. Customers are intuitively expecting to gain more benefits if they can actively participate and contribute to others within the community. Incentives should be provided in a fair manner. Different from the discussed fairness in the few literatures, where [55] defines it as assigning the long-term average delay equally for each user and [56] addresses it as social fairness, we propose the *fairness* based on the participation level. The participation level has been utilized by cooperation [57] in business to distribute benefits accordingly. In other words, the fairness in this chapter is defined as "customers with higher participation level can reduce their individual cost (as the distributed benefits in cooperation) more than those with lower participation level within the same community". To achieve this *fairness*, customizing trading prices for customers according to the participation level is an effective approach.

A fair demand response with electric vehicles (F-DREV) is proposed for the cloud based energy management service, based on our previous work [30]. Inheriting the characteristics of the cloud based energy management service, F-DREV can be adopted by existing REPs or utilities, and is flexible, scalable, reconfigurable and cost-efficient. The interoperability is shown by considering DER, EV with V2G, storage, and multiple loads (fixed, interruptible and non-interruptible) in this chapter. The proposed fairness is maintained by customizing trading prices for each customer according to the customer's participation level and other involved customers. It is related to the production capacity of DER and the flexibilities of requested loads. Customer who invests the DER more can acquire higher participation level and more return of the original investment (i.e., reduced individual cost). With the formed community and customized trading prices, choices of electricity usage and trading are combined for customers. Due to the increasing complexity of massive combinations, finding the optimal choices for customers within the community is non-trivial. A binary linear programming model is formulated for F-DREV facilitating among customers within the community to determine the optimal choices for each customer in the given time periods. F-DREV achieves two goals for each community: 1) maximizing incentives as minimizing the global cost while maintaining the proposed fairness for each customer, and 2) smoothing the fluctuation within the community according to commitments, which are similar to existing contracts between REPs [12] and utilities. According to the determined optimal choices for entire community in the following time periods and the commitments, utilities (i.e., power companies) can schedule and control their conventional generators efficiently.

The contributions of this chapter are summarized as follow. (i) To the best of our knowledge, this is the first work that proposes fairness as "customers with higher participation level can reduce their individual cost more than those with lower participation level within the same community" for the demand response and EV charging scheduling. The participation level is quantified by a fairness index and utilized to customize the trading prices. Incentives are directed to customers for actively controlling their consumption patterns and investing DER. (ii) F-DREV realizes the demand response and EV charging scheduling in the cloud based energy management service [30]. Choices of electricity usage and trading are combined and determined optimally to achieve the minimized global cost as the maximized incentives for each community, which is formed by involved customers owning various combination of DER, EV, storage, and multiple load types. Fluctuation within each community can be smoothed accordingly to operate DERs and EVs within the community grid-friendly, and help utilities managing their generators scheduling more efficiently. (iii) A binary linear programming model is formulated, and detailed performances are evaluated with different experiments.

The remainder of this chapter is organized as follows: the system model is introduced in Section 4.4, and the formulated binary linear programming model is presented in Section 4.5. Performance evaluation is discussed in Section 4.6, and conclusions are summarized in Section 4.7.

4.4 System Model

F-DREV realizes the fair demand response and EV charging scheduling for the cloud based energy management service, and extends the system model from [30]. The following subsections firstly introduce the extended framework and the load types. Then fairness indexes are presented to quantify participation levels, and price indicators are discussed with the customized trading prices. Last, the procedure of operating F-DREV for each community is illustrated.

4.4.1 Extended Framework

The extended framework is illustrated in Fig. 4.1. It is constructed by the F-DREV provider, a power grid, conventional power companies and multiple communities. F-DREV is operated on the cloud infrastructure to serve multiple communities through the thin client interface, i.e., web browsers or application programming interface (API). The power grid is supported by DERs within communities and conventional power companies with various conventional generators. Different service plans are provided by the F-DREV provider, and are similar to the various plans provided by existing REPs. Customers can choose to join a service plan by agreeing the benefits and rules in contract to F-DREV provider. Then they become customers of a certain community that is formed by other customers who also joined the same service plan. In other words, communities are formed by customers involved in the same service plan, and have different requirements and benefits (i.e., trading prices among customers). Each customer stands for various sizes of household, from single to multiple ones. In our framework, F-DREV is provided to customers owning various combinations of three components: DER, storage and EV. To simplify, three types of customer in Table 4.1 are considered in this chapter, and customers own at most one of each component. The considered components are discussed blow.

4.4.2 Framework

4.4.2.1 DERs

are focusing on small-scale non-dispatchable distributed renewable energy generators, such as the solar arrays equipped on rooftops. They are connected to the power grid following the interconnection agreements with local electric transmission and distribution

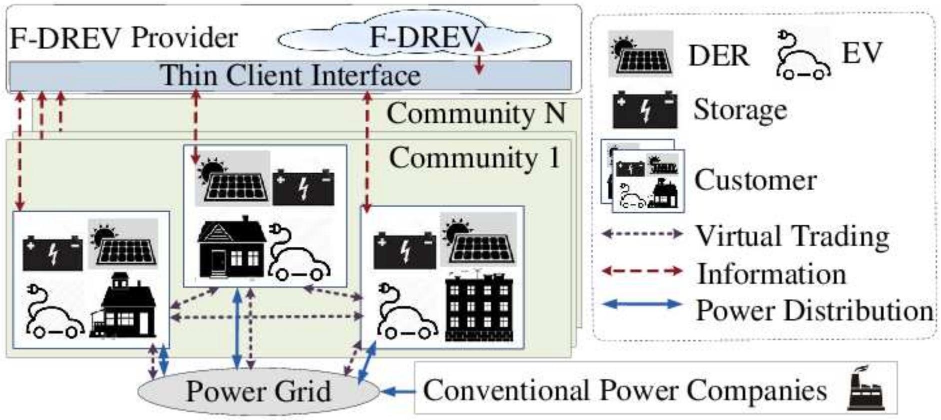

Figure 4.1: Framework

Table 4.1: Customer types

Customer type	DER	Storage	EV	V2G
1.	1	1	1	1
2.	1	1	1	0
3.	1	1	0	0

utilities [37]. Each DER has a set of choice variables, $\{E^{rm}, E^{rc}, E^{re}, E^{rs}, E^{rd}\}$ with its production capacity G.

4.4.2.2 Storages

are able to be powered by both DERs and conventional generators, and the (dis)charging efficiency are indicated as ηd^s and ηc^s respectively. It is assumed can be store and release energy quickly in this chapter. The minimum and maximum storage capacities are denoted as S^{min} and S^{max}. Each storage system comes with two sets of choice variables: $\{I^{ms}, I^{cs}, I^{rs}, I^{es}\}$ and $\{E^{sm}, E^{sc}, E^{se}, E^{sd}\}$.

4.4.2.3 EVs

are not limited to the charging scenario. They also have the ability of providing energy back to the power grid, which is known as V2G [58]. Each EV has a set of importing choice variables $\{I^{me}, I^{ce}, I^{se}, I^{re}\}$, and another set of exporting choice variables

$\{E^{em}, E^{ec}, E^{es}, E^{ed}\}$ exists when it has the V2G ability. Depending on different driving behaviors and schedules, each EV connects to F-DREV at the arriving time α^e with the initial capacity EV^{init} in its battery, and disconnects at the leaving time β^e with the required capacity EV^{end}. The (dis)charging efficiencies are denoted as ηd^e and ηc^e with the rate γ^e. The minimum and maximum capacity are denoted as $S^{e,min}$ and $S^{e,max}$.

4.4.3 Load Types

Multiple fixed loads and deferrable loads are considered to be requested by each customer in this chapter. Fixed loads cannot be shifted and are required to be able to turn on and off immediately (e.g., television and computers). The summation of every fixed load is denoted as D. Deferrable loads can be divided up into interruptible load (e.g., space cooling/heating) and non-interruptible load (e.g., washing machine and dryer). Interruptible load has higher flexibility since its operation can be delayed and is able to shut down or turn on after it is active. The operation of non-interruptible load can be delayed as well, but requires to remain active until the load is fulfilled. In this chapter, deferrable load is formulated depending on its required operating time R, power consumption rate γ, and the allowed operating time frame form α to β. The values of the prior two (R, γ) are based on the standard of various appliances, and the latter two (α, β) can be assigned by customers directly.

A binary control variable O^{il} is used to indicate the operating status for each interruptible load at each time step. It is set to 1 when the interruptible load is activated, and its summation over the allowed operating time frame has to be equal to the required operating time, as shown in (4.1).

$$\sum_{t=\alpha_{i,j}^{il}}^{\beta_{i,j}^{il}} O_{i,j,t}^{il} = R_{i,j}^{il}, \forall i \in \mathbb{N}, \forall j \in \mathbb{IL}_i. \tag{4.1}$$

For each non-interruptible load, the operating statuses are indicated by a binary control variable O^{nl} at each time step. Similar to (4.1), the summation of the activated status over the allowed operating time frame is equal to the required operating time in (4.2). Moreover, to ensure the continuity of non-interruptible loads, another binary control variable O^a is brought in to denote the starting time of activating the load. Only one starting time exists between time α and $\beta - R + 1$ as shown in (4.3). Once the starting time is determined at time t, the O^{nl} between time step t and $t + R - 1$ need to be 1 to maintain the continuity. This relationship is presented in (4.4), and can be transformed to (4.5) to eliminate the non-linearity.

$$\sum_{t=\alpha_{i,j}^{nl}}^{\beta_{i,j}^{nl}} O_{i,j,t}^{nl} = R_{i,j}^{nl}, \forall i \in \mathbb{N}, \forall j \in \mathbb{NL}_i. \tag{4.2}$$

$$\sum_{t=\alpha_{i,j}^{nl}}^{\beta_{i,j}^{nl}-R_{i,j}^{nl}+1} O_{i,j,t}^{a} = 1, \forall i \in \mathbb{N}, \forall j \in \mathbb{NL}_i. \tag{4.3}$$

$$\sum_{t=\alpha_{i,j}^{nl}}^{\beta_{i,j}^{nl}-R_{i,j}^{nl}+1} O_{i,j,t}^{a} \times \sum_{t'=t}^{t+R_{i,j}^{nl}-1} O_{i,j,t'}^{nl} = R_{i,j}^{nl}, \forall i \in \mathbb{N}, \forall j \in \mathbb{NL}_i. \tag{4.4}$$

$$O_{i,j,t'}^{nl} - O_{i,j,t}^{a} = 0, t = \alpha_{i,j}^{nl}, ..., \beta_{i,j}^{nl} - R_{i,j}^{nl} + 1, t' = t, ..., t + R_{i,j}^{nl} - 1, \forall i \in \mathbb{N}, \forall j \in \mathbb{NL}_i. \tag{4.5}$$

4.4.4 Fairness Index

In this chapter, fairness is defined as "customers with higher participation level can reduce their individual cost more than those with lower participation level within the same community". The participation level has been used by cooperative [57] to distribute benefits to members accordingly. To achieve the proposed fairness, trading prices are customized for each customer according to a fairness index (F) that quantify the participation level over the given time periods. The customized trading prices P^{rs} and P^{rb} will be discussed in detail in subsection 4.4.5 with other price indicators.

Fairness index is designed as the forecasted DER's production capacity (G) multiplying the flexibility ($Flex$) of total requested loads, as shown in (4.6). Customers with larger production capacity of DER have more chance to participate by initiating the trading to others within the community. The DER production capacity depends on the original investment and is affected by the different conditions of each DER (e.g., local weather, angles of DER). Likewise, customers with higher flexibility of their requested loads are able to participate more by adjusting the operating time. Thus, their fairness indexes would be higher.

$$F_i = \sum_{t \in \mathbb{T}} \{G_{i,t}\} \times Flex_i, \forall i \in \mathbb{N}. \tag{4.6}$$

$Flex$ is expressed in (4.7) as the summation of four terms, indicated for fixed load, interruptible loads, non-interruptible loads, and EV load sequentially. The denominator for each term is the total requested amount times a weight. For the deferrable loads, the total requested amount is calculated as the summation of each deferrable load's required operating time R multiplied by the power consumption rate γ. Three weights (w^{fl}, w^{il}, w^{nl}) are used to distinguish fixed, interruptible, and non-interruptible loads respectively. Due to the similar behavior of EV load to interruptible load, w^{il} is also used for EV loads. The numerator in each term of $Flex$ depends on the allowed operating time frame. It is set to 1 for fixed load, and is calculated as the allowed operating time frame $(\beta - \alpha + 1)$ minus the required operating time for deferrable loads and EV loads.

$$\begin{aligned} Flex_i = \sum_{t \in \mathbb{T}} (\frac{1}{w^{fl} D_{i,t}}) + \frac{\sum_{j \in \mathbb{IL}_i} (\beta^{il}_{i,j} - \alpha^{il}_{i,j} + 1 - R^{il}_{i,j})}{w^{il} \sum_{j \in \mathbb{IL}_i} (\gamma^{il}_{i,j} R^{il}_{i,j})} + \frac{\sum_{j \in \mathbb{NL}_i} (\beta^{nl}_{i,j} - \alpha^{nl}_{i,j} + 1 - R^{nl}_{i,j})}{w^{nl} \sum_{j \in \mathbb{NL}_i} (\gamma^{nl}_{i,j} R^{nl}_{i,j})} \\ + \frac{\beta^e_i - \alpha^e_i + 1 - \lceil \frac{EV^{init}_i - EV^{end}_i}{\gamma^e_i} \rceil}{w^{il} (EV^{init}_i - EV^{end}_i)}. \end{aligned} \tag{4.7}$$

4.4.5 Price Indicators

$\{P^b, P^s, P^u, P^l, P^{rs}, P^{rb}, P^e\}$ are seven price indicators used by F-DREV, where the cost of electricity and environment are included in the first six price indicators to promote the usage of renewable energy. P^b is the price of buying energy that is supported by conventional generators from the power grid. It is provided as a known input value for each time step via the prediction in real-time electricity pricing or the regulating retail prices that depend on service provider and utilities. It is similar to the provided selling prices by the existing REP. The price of selling produced renewable energy to the power grid is P^s. It can be viewed as a smaller value than P^b since it excludes the environment cost, such as CO_2 emission cost or tax savings provided by government [59]. The relationship between P^b and P^s is shown in (4.8), where λ depends on various environment penalties in each region.

P^u and P^l appear with value between P^b and P^s when the community is formed. Similar to the new appeared price in [30] and the price provided by existing REP, they are assigned by contracts that are agreed between customers and F-DREV provider. As mentioned in subsection 4.4.2, they could be different values for each community. The agreed P^u and P^l are utilized by F-DREV to customize the trading prices (P^{rs}, P^{rb}) for each customer based on the customer's individual fairness index as discussed in subsection 4.4.4 and other involved customers. Both P^{rs} and P^{rb} are guaranteed to be the values between P^u and P^l as interpreted in (4.9) and (4.10). N is the total number of customers in the community, and $rank\{F_i\}$ is the ranking of individual fairness index within the community. Customer with the highest fairness index in the community will acquire the largest ranking, and able to obtain the largest P^{rs} and smallest P^{rb}. The proposed fairness can be shown instinctively since customers with higher participation level have advantage of reducing their individual cost more than others by initiating the trading to others with the customized price.

$$P_t^s = \lambda P_t^b \qquad ,0 < \lambda < 1, \forall t \in \mathbb{T}. \tag{4.8}$$

$$P_{i,t}^{rs} = P_t^l + \frac{rank\{F_i\}}{N}(P_t^u - P_t^l) \qquad ,\forall i \in \mathbb{N}, \forall t \in \mathbb{T}. \tag{4.9}$$

$$P_{i,t}^{rb} = P_t^u - \frac{rank\{F_i\}}{N}(P_t^u - P_t^l) \qquad ,\forall i \in \mathbb{N}, \forall t \in \mathbb{T}. \tag{4.10}$$

P^e is the price of exporting energy from EVs, and is interpreted as the cost of battery degradation in V2G technologies in this chapter. It depends on the amount and rate of

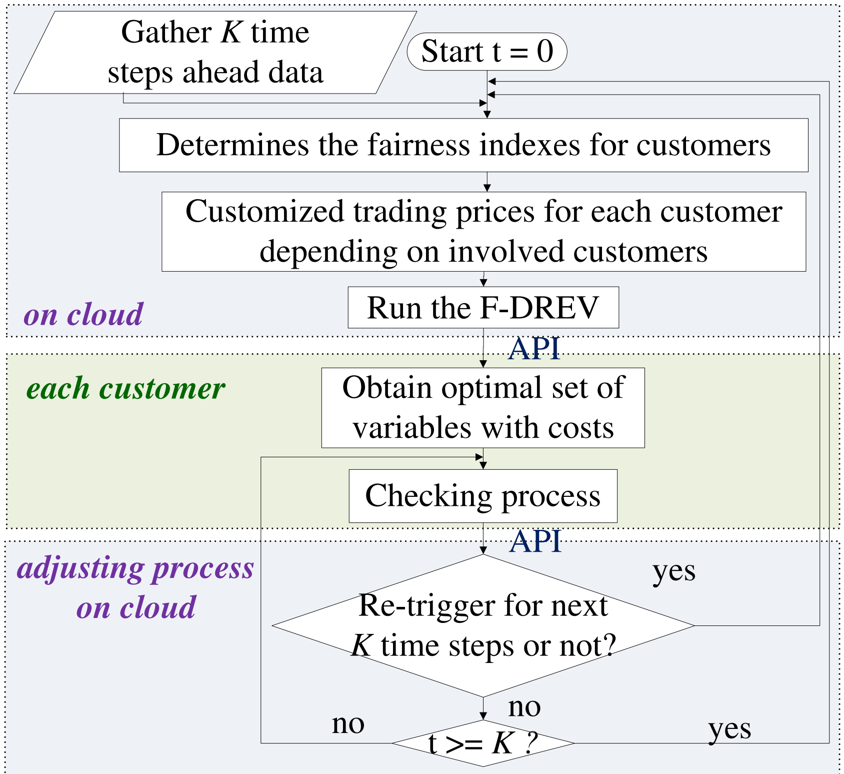

Figure 4.2: Procedure

energy withdrawn and is a function of discharge depth discharge and cycling frequency [60]. For simplification, we assume it can be acquired as a known value in advance.

4.4.6 Procedure

The procedure of operating F-DREV for one community is shown in Fig. 4.2. Firstly, F-DREV provider actively operates on the cloud infrastructure to gather K time steps ahead data, which includes $\{G, T^c, P^b, P^s, P^u, P^l, P^e\}$ and all the parameters of components and loads. They are provided to F-DREV as know values via forecast technics (G, P^b, P^s), directly input from customers (P^e, parameters of components and loads) or the agreed contracts (P^u, P^l, T^c), where T^c is the assigned capacity for each power distribution line. T^c is provided by local utilities, and depends on the physical distribution network which supports both customers and non-customers of F-DREV.

After acquiring the above data, fairness indexes are determined via (4.6) for each customer. Depending on other involved customers within the community, the individual fairness indexes are utilized for customizing trading prices for each customer. Then, the proposed F-DREV will be run to find the optimal global cost for each community and inform the determined optimal set of variables to each customer through APIs. With the received optimal set of variables, each customer operates the requested loads, and (dis)charges storage and EV accordingly for the following given K time steps through advanced smart home appliances. A mapping mechanism is used to realize the virtual trading within community. Local utility will only receive the mapped amount of requested energy by each customer as $(A_{i,t})$ in (4.11), which is similar to the requests made from non-F-DREV customers.

$$\begin{aligned} A_{i,t} = {} & I^{md}_{i,t} + I^{cd}_{i,t} + I^{ms}_{i,t} + I^{cs}_{i,t} + I^{me}_{i,t} + I^{ce}_{i,t} - E^{rm}_{i,t} - E^{rc}_{i,t} - \eta d^s E^{sc}_{i,t} \\ & - \eta d^s E^{sm}_{i,t} - \eta d^e E^{ec}_{i,t} - \eta d^e E^{em}_{i,t}, \forall i \in \mathbb{N}, \forall t \in \mathbb{T}. \end{aligned} \tag{4.11}$$

To deal with uncertainties (e.g., unpredicted changes in electricity usage or unscheduled operations) and forecast errors, two processes (checking process and adjusting process) are included after each customer obtaining the optimal sets of variables as shown in Fig. 4.2. The real-time data is checked by customers for each adjustment interval in the checking process, and is used by service provider to determine whether to trigger the F-DREV for the next K time steps or not in the adjusting process. These two processes are adopted from our previous work [30], where the complete information can be found.

4.5 Formulation

A binary linear programming model is formulated for F-DREV minimizing the global cost with the customized trading prices and smoothing the fluctuation for each community. Variables of the model are listed in nomenclature, which include three binary control variables and the choice variables for components (DER, storage, EV) and loads. The operation costs of components are assumed to be negligible in this chapter.

The objective function in (4.12) is minimizing the global cost for each community over K time steps. It is interpreted as the summation of each customer's individual cost, which includes the cost of satisfying requested loads ($C^d_{i,t}$), trading within the community ($C^r_{i,t}$), utilizing the storage system ($C^s_{i,t}$) and EV ($C^e_{i,t}$). They are shown in (4.13)-(4.16) respectively.

$$\text{Minimize} \sum_{t\in\mathbb{T}} (\sum_{i\in\mathbb{N}} (C^d_{i,t} + C^r_{i,t} + C^s_{i,t} + C^e_{i,t})) \tag{4.12}$$

$$C^d_{i,t} = I^{md}_{i,t} P^b_t + I^{cd}_{i,t} P^{rb}_{i,t} \tag{4.13}$$

$$C^r_{i,t} = -E^{rm}_{i,t} P^s_t - E^{rc}_{i,t} P^{rs}_{i,t} \tag{4.14}$$

$$C^s_{i,t} = I^{ms}_{i,t} P^b_t + I^{cs}_{i,t} P^{rb}_{i,t} - \eta d^s E^{sm}_{i,t} P^s_t - \eta d^s E^{sc}_{i,t} P^{rs}_{i,t} \tag{4.15}$$

$$C^e_{i,t} = I^{me}_{i,t} P^b_t + I^{ce}_{i,t} P^{rb}_{i,t} - \eta d^e E^{em}_{i,t} (P^s_t + P^e_t) - \eta d^e E^{ec}_{i,t} (P^{rs}_{i,t} + P^e_t) \tag{4.16}$$

The objective function subjects to several constraints, where (4.1)-(4.3) and (4.5) are included to assure the requirements of deferrable loads. For each customer at each time step, (4.17) guarantees the total requested amount of energy can be fulfilled. Constraint (4.18) shows the summation of requested energy, $A_{i,t}$ in (4.11), from customers connected to the same z_{th} power distribution line cannot exceed the assigned capacity for the corresponding power distribution line (T^c_z).

$$D_{i,t} + (\sum_{j\in\mathbb{IL}_i} \gamma^{il}_{i,j} O^{il}_{i,j,t}) + (\sum_{j\in\mathbb{NL}_i} \gamma^{nl}_{i,j} O^{nl}_{i,j,t}) = I^{md}_{i,t} + I^{cd}_{i,t} + I^{rd}_{i,t} + I^{sd}_{i,t} + I^{ed}_{i,t}, \forall i, \forall t. \tag{4.17}$$

$$\sum_{i\in\mathbb{L}_z} A_{i,t} \leq T^c_{z,t}, \forall z, \forall t. \tag{4.18}$$

The exported energy from each DER is assured to be same as its production capacity in (4.19). Constraint (4.20) prevents customers from exporting more than the import amount of energy from the community to avoid customers with higher participation level potentially making profit by exporting the produced renewable energy to the community with higher P^{rs} and import the required amount from the community with lower

P^{rb}. Constraint (4.21) tracks the available power within the community to prevent the requested amount within the community surpass the available amount.

$$G_{i,t} = E^{rm}_{i,t} + E^{rc}_{i,t} + E^{re}_{i,t} + E^{rs}_{i,t} + E^{rd}_{i,t}, \forall i, \forall t. \tag{4.19}$$

$$E^{rc}_{i,t} - I^{cd}_{i,t} - I^{ce}_{i,t} - I^{cs}_{i,t} \leq 0, \forall i, \forall t. \tag{4.20}$$

$$\sum_{i \in \mathbb{N}} \eta d^s E^{sc}_{i,t} - I^{cs}_{i,t} + E^{rc}_{i,t} + \eta d^e E^{ec}_{i,t} - I^{ce}_{i,t} - I^{cd}_{i,t} = 0, \forall t. \tag{4.21}$$

Constraints (4.22)-(4.25) are related to the storage, where (4.22) shows the state variable (S) depends on the previous state variable and variables in the current time step. (4.23) and (4.24) describe that the state variable can only operate in the range from S^{min} to S^{max} after exporting energy at each time step. (4.25) shows the exported amount of energy cannot exceed the previous imported amount of energy from DREs and community. It indicates only the energy that is imported from the DERs can be sold with the trading price (P^{rs}) that excludes the environment cost. align

$$S_{i,t+1} = S_{i,t} + \eta c^s \times (I^{ms}_{i,t} + I^{cs}_{i,t} + I^{rs}_{i,t} + I^{es}_{i,t}) - (E^{sm}_{i,t} + E^{sc}_{i,t} + E^{se}_{i,t} + E^{sd}_{i,t}), \forall i, \forall t. \tag{4.22}$$

$$S_{i,t} - E^{sm}_{i,t} - E^{sc}_{i,t} - E^{se}_{i,t} - E^{sd}_{i,t} \geq S^{min}_i, \forall i, \forall t. \tag{4.23}$$

$$S^{min}_i \leq S_{i,t} \leq S^{max}_i, \forall i, \forall t. \tag{4.24}$$

$$\sum_{t'=1}^{t-1} (\eta^{sc} I^{rs}_{i,t'} + \eta^{sc} I^{cs}_{i,t'} - E^{sc}_{i,t'}) - E^{sc}_{i,t} \geq 0, \forall i, \forall t. \tag{4.25}$$

Constraints (4.26)-(4.34) are related to the EV. The initial capacity for each EV is assigned to its state variable (S^e) at the arriving time in (4.26), and (4.27) guarantees it can acquire larger or equal to the required capacity at the leaving time. Constraints (4.28)-(4.30) show the state variable of EV equals to 0 when it is not connecting to the F-DREV, and is always larger or equal to the minimum capacity after exporting energy. The state variable is constrained by (4.31) to operate in the range between $S^{e,min}$ and $S^{e,max}$. The relationship among (dis)charging rate, variables and efficiency are presented in (4.32) and (4.33). Similar to (4.25), (4.34) guarantees the exported amount of energy cannot exceed the previous imported power from DERs and community. If customers don't own the EV, all the variables for EV are equal to 0. Likewise, if the owned EV doesn't have the V2G ability, the variables related to the exporting are equal to 0.

$$S^{e}_{i,t} = EV^{init}, t = \alpha_i, \forall i, \forall t. \tag{4.26}$$

$$S^{e}_{i,t} \geq EV^{end}, t = \beta_i, \forall i, \forall t. \tag{4.27}$$

$$S^{e}_{i,t} = 0, t = 0, 1, ..., \alpha_i - 1, \text{and } \beta_i + 1, \beta_i + 2, ..., K, \forall i, \forall t. \tag{4.28}$$

$$\sum_{t'=1}^{t-1} (\eta c^e I^{re}_{i,t'} + \eta c^e I^{ce}_{i,t'} - E^{ec}_{i,t'}) - E^{ec}_{i,t} \geq 0, \forall i, \forall t. \tag{4.29}$$

$$S^{e}_{i,t} - (E^{em}_{i,t} + E^{ec}_{i,t} + E^{es}_{i,t} + E^{ed}_{i,t}) \geq S^{e,min}, \forall i, \forall t. \tag{4.30}$$

$$S^{e,min} \leq S^{e}_{i,t} \leq S^{e,max}, \forall i, \forall t. \tag{4.31}$$

$$\eta c^e \times (I^{me}_{i,t} + I^{ce}_{i,t} + I^{se}_{i,t} + I^{re}_{i,t}) \leq \gamma^e_i, \forall i, \forall t. \tag{4.32}$$

$$\eta d^e \times (E^{em}_{i,t} + E^{ec}_{i,t} + E^{es}_{i,t} + E^{ed}_{i,t}) \leq \gamma^e_i, \forall i, \forall t. \tag{4.33}$$

$$\begin{aligned} S^{e}_{i,t+1} = S^{e}_{i,t} + \eta c^e (I^{me}_{i,t} + I^{ce}_{i,t} + I^{se}_{i,t} + I^{re}_{i,t}) - (E^{em}_{i,t} + E^{ec}_{i,t} \\ + E^{es}_{i,t} + E^{ed}_{i,t}), t = \alpha_i, \alpha_i + 1, ..., \beta_i - 1, \forall i, \forall t. \end{aligned} \tag{4.34}$$

Constraints (4.35)-(4.41) indicate the exported amounts between customers' components need to match the corresponding imported amount with the efficiency rate.

$$I^{rd}_{i,t} - E^{rd}_{i,t} = 0, \forall i, \forall t. \tag{4.35}$$

$$I^{re}_{i,t} - E^{re}_{i,t} = 0, \forall i, \forall t. \tag{4.36}$$

$$I^{rs}_{i,t} - E^{rs}_{i,t} = 0, \forall i, \forall t. \tag{4.37}$$

$$I^{es}_{i,t} - \eta d^e_i E^{es}_{i,t} = 0, \forall i, \forall t. \tag{4.38}$$

$$I^{ed}_{i,t} - \eta d^e_i E^{ed}_{i,t} = 0, \forall i, \forall t. \tag{4.39}$$

$$I^{se}_{i,t} - \eta d^s_i E^{se}_{i,t} = 0, \forall i, \forall t. \tag{4.40}$$

$$I^{sd}_{i,t} - \eta d^s_i E^{sd}_{i,t} = 0, \forall i, \forall t. \tag{4.41}$$

T^u and T^l are the upper and lower bound to smooth the fluctuation within the community. Through the coordination among every component from customers, the fluctuated

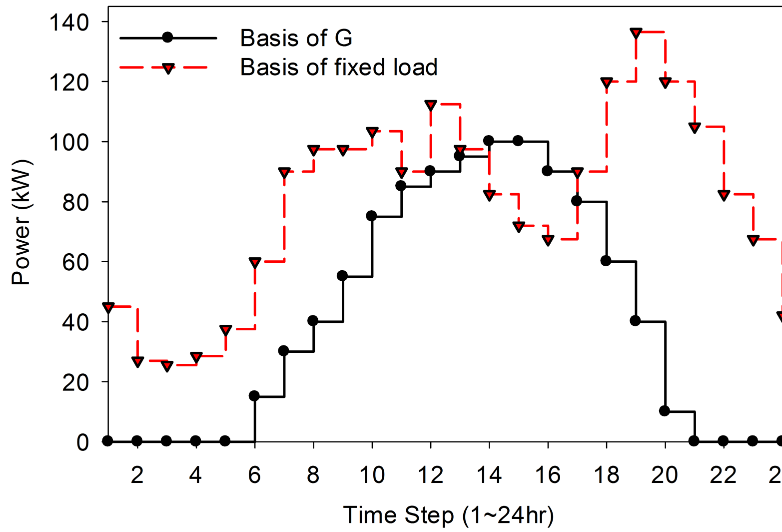

Figure 4.3: Basis for the DER production capacity and fixed loads

penetration of EV loads and production capacities from DERs could be complemented to allow EVs and DERs within the community operate grid-friendly. It can be interpreted as the total imported energy from the power grid, and is bounded in (4.42). Less capacity needs to be reserved by the conventional generators when the difference between T^u and T^l is smaller.

$$T^l_t \leq \sum_{i\in\mathbb{N}}\{I^{md}_{i,t} + I^{ms}_{i,t} + I^{me}_{i,t} - E^{rm}_{i,t} - \eta d^s E^{sm}_{i,t} - \eta d^e E^{em}_{i,t}\} \leq T^u_t, \forall t. \tag{4.42}$$

The formulated binary linear programming model is solved by IBM ILOG CPLEX Optimizer 12.6 [43] in this chapter with all variables greater or equal to 0.

4.6 Performance Evaluation

4.6.1 Experiment Environment

Experiments are conducted in the hourly day-ahead operation interval, where a time step is an hour and K equals to 24. Three types of customer in Table 4.1 form a community, and each customer stands for various sizes of household. The production

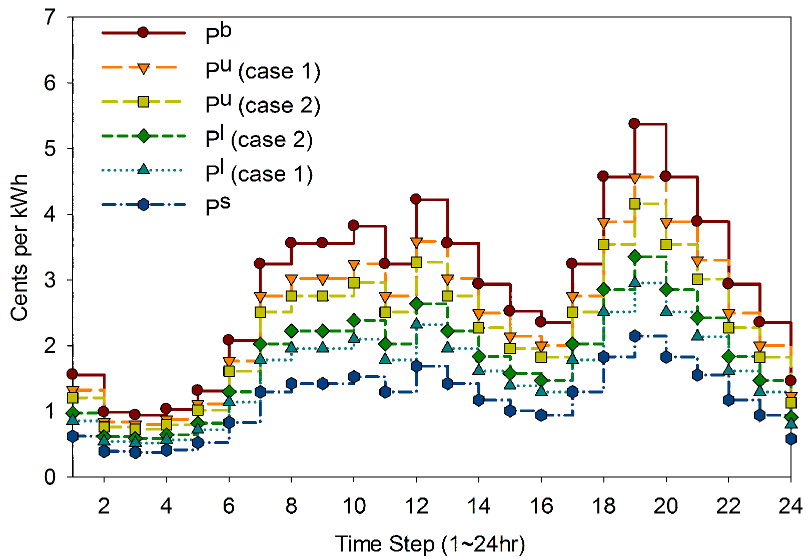

Figure 4.4: Utilized P^b, P^u, P^l, P^s in experiment

Table 4.2: Experiment parameters setting

# of $j \in \mathbb{IL}, \mathbb{NL}$	$\mathcal{U}(1,5)$	w^{fl}, w^{nl}, w^{il}	$3, 2, 1$
R	$\mathcal{U}(1,3)$	S^{max}	10 kWh
γ^{nl}, γ^{il}	$\mathcal{U}(1,5)$	S^{min}	$15\% \times S^{max}$
α^{nl}, α^{il}	$\mathcal{U}(1, K-R)$	ηd^s, ηc^s	0.96
β^{nl}, β^{il}	$\mathcal{U}(\alpha+R, K)$	$S^{e,max}$	24 kWh
P^e	130 \$ per MWh	$S^{e,min}$	$20\% \times S^{e,max}$
α^e	$\mathcal{U}(8,16)$	ηd^e, ηc^e	0.95
EV^{init}	$\mathcal{U}(1,4)$	γ^{ev}	4 kWh
β^e	$\mathcal{U}(\alpha + \lceil (EV^{init} - EV^{end}) \rceil, K)$		
EV^{end}	$\mathcal{U}(EV^{init}+4, EV^{init}+20)$		

capacity of each customer's DER follows the basis in Fig. 4.3, according to the database of CAISO [61] that solar generations are able to work from clock 6 to 20 a day in summer. Depending on the different DER configurations, the G for each DER is calculated as the basis times a uniform distribution. To represent the environment of low and high DER production capacities among the community, $\mathcal{U}(0.2, 1.2)$ and $\mathcal{U}(0.8, 1.8)$ are two uniform distributions used for scenario 1 and 2 respectively. Each customer has multiple fixed, non-interruptible and interruptible loads. The grouped fixed loads are designed based on a basis of load profile, which is showed in Fig. 4.3. They are calculated by multiplying the basis with a uniform distribution, which represents various preferences and different sizes of households. Parameters of non-interruptible, interruptible loads and weights are listed in Table 4.2. Customers connect to different power distributions lines (e.g., branches from multiple feeders) uniformly. In the experiment, we assume there is no blackout situation and design the assigned capacity of each power distribution line (T^c) as the number of connected customers times 150 kW, which is slightly larger than the maximum value in the basis of load profile.

Price indicators are provided as known values via various forecasting methods [62] and the agreed contracts as discussed in subsection 4.4.5. To make the experiment environment more realistic, we assume F-DREV acquires P^b based on the predicted fuel cost from a conventional generator, which produces sufficient energy to support loads for 3600 residents including both non-customers and customers of F-DREV under its output capacity constraints from 100 MW to 500 MW. With a quadratic fuel cost function that is widely used in thermal power plants [41], P^b is calculated as $a + b(3600 \times$ load basis$) + c(3600 \times$ load basis$)^2$ with the coefficients $(a, b, c) = (240, 7, 0.007)$. The values are between 0.9 and 5.4 cents per kWh. λ is set to 0.4 for P^s in (4.8). To illustrate the effect of different designs of P^u and P^l, two cases of these two price indicators are discussed. The first case of P^u is equal to $P^s + \frac{3}{4}(P^b - P^s)$, and P^l is equal to $P^s + \frac{1}{4}(P^b - P^s)$. In the second case, P^u is set to $P^s + \frac{5}{8}(P^b - P^s)$, and P^l is equal to $P^s + \frac{3}{8}(P^b - P^s)$. Since the design of P^u and P^l directly affects the distinction of the proposed fairness in each community, both cases are discussed in the evaluation of fairness performance in subsection 4.6.5. For other performance evaluations, the first case of P^u, P^l is used. The utilized time variant price indicators, $\{P^b, P^u, P^l, P^s\}$, over 24 time steps are presented in Fig. 4.4. The price of P^e follows the battery degradation cost in [63] as listed in Table 4.2.

The real experiment implementations are considered in the chapter, where the spec of tesla home battery [64] is utilized for the vale of $S^{max}, \eta d^s$ and ηc^s. According to [65],

S^{min} is set as 15% of S^{max}. The value of γ^e, ηd^e, ηc^e, $S^{e,max}$ and $S^{e,min}$ of each EV follow the summarized data from three types of EV fleet data based on a European scenario in [46], where $S^{e,min}$ is 20% of $S^{e,max}$. Values of these parameters are presented in Table 4.2, which also lists EV^{init}, EV^{end}, α^e and β^e for the simplified driving behavior of each EV.

4.6.2 Comparison Schemes

Two comparison schemes are implemented to evaluate the performance of F-DREV. The first scheme, IM, manages loads individually without forming the community. It is similar to the approaches used in unmanaged distributed generators [66] and home energy management systems [48]. Trading is not available among customers, and choice variables are made based on the owned components, loads and fluctuated price indicator (P^b, P^s) individually for each customer.

The second scheme, DREV, fully coordinates the formed community without discriminating trading price for individual customer. That is, the trading price within the community in DREV is same for every customer. In the experiment, the trading price (P^r) in the compared DREV is chosen as the value that is able to achieve the least cost for each community. It should be the value that provides the same incentive (i.e. $P^b - P^r$ and $P^r - P^s$) for both customers who want to buy and who want to sell. If setting P^r as the value closer to P^b, P^r has more chance larger than P^b in different time steps. It decreases the willingness for customers buying from others, and increases the global cost. Similarly, if setting P^r as the value closer to P^s, lower incentive will be provided for customers selling to others and the global cost will be larger. Thus, the least-cost trading price is set to the value that satisfies $(P^b_t - P^r_t) = (P^r_t - P^s_t)$. To verify this, an experiment is conducted for 500 customers under scenario 1 of DER production capacity to show the global cost that achieved by DREV schemes with three different trading prices. As expected, the case with least-cost trading price achieves the smallest

Table 4.3: Requirements of deferrable loads

	Interruptible load					Non-interruptible load
	no. 1	no. 2	no. 3	no. 4	no. 5	no. 1
α	10	15	5	21	1	8
β	13	22	17	24	20	21
γ	2	2	4	3	1	2
R	3	3	2	3	3	2

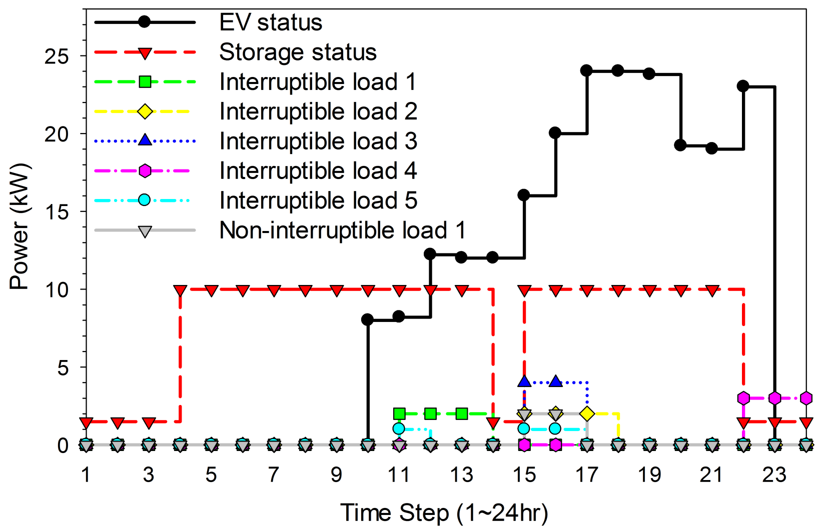

Figure 4.5: The schedule of EV, storage, and deferrable loads

global cost as \$20549.15. The cases with the trading prices as the first case of P^u and P^l, which are mentioned in subsection IV-A, achieve larger costs as \$20558.73 and \$20558.98 respectively.

4.6.3 Illustration of a customer's schedules and interactions

We extract the information from a type 1 customer (the 87_{th}) out of 500 customers under scenario 2 (high DER production capacity) to present the schedule of storage, EV, and deferrable loads. The arriving time of the owned EV is time step 10 with initial capacity 8 kWh, and the leaving time step is 22 with required capacity 23 kWh. $\eta d^e, \eta c^e$ and γ^e follow the setting in Table 4.2. Five interruptible loads and one non-interruptible

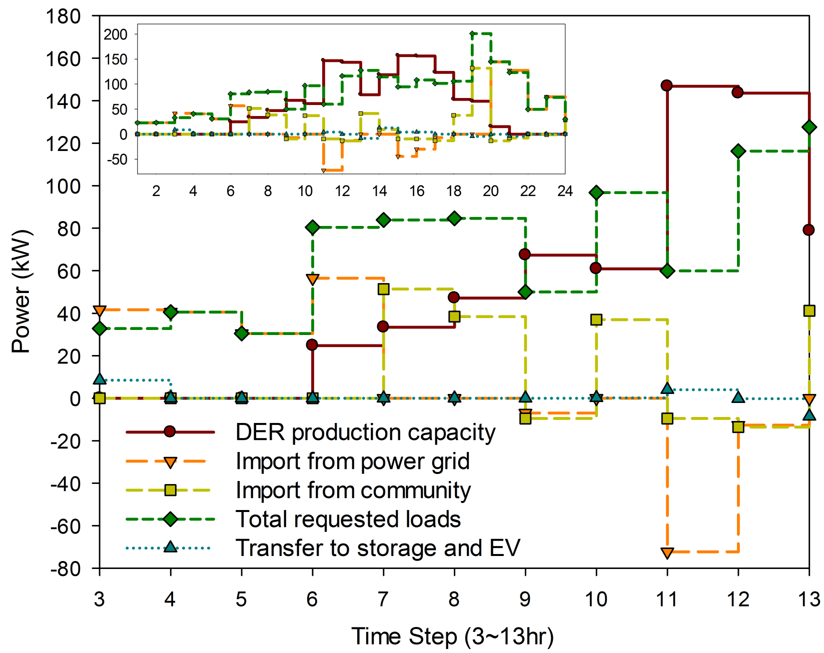

Figure 4.6: Interactions among customer's components, power grid, and community

load are requested with details listed in Table 4.3. The determined operating time for each deferrable load, and the (dis)charging status of both storage and EV are presented in Fig. 4.5. Both storage and EV are operated between their maximum and minimum capacities, and EV is connected according to its arriving and leaving time. Deferrable loads are scheduled between their allowed operating time frame, and non-interruptible load maintains its continuity requirement. For example, interruptible load 5 is scheduled to operate at time step 11, 15 and 16, and non-interruptible load 1 is assigned to operate at time step 15 and 16.

To illustrate the interactions among customer's components, power grid, and the belonged community, Fig. 4.6 presents the amount of the total requested loads (includes fixed loads and scheduled deferrable loads), DER production capacity, the imported energy from both power grid and community, and the transferred amount to storage and EV from time step 3 to time step 13. Information over 24 time steps is also presented in the upper left part of the figure. Examples are shown in the Fig. 4.6 such as the

Table 4.4: Global cost savings performance

	Scenario 1			Scenario 2		
Customer #	IM	DREV	F-DREV	IM	DREV	F-DREV
500	1.069	1.055	1	1.187	1.142	1
1000	1.067	1.054	1	1.184	1.140	1
1500	1.068	1.054	1	1.184	1.140	1

customer imports power from the power grid for the requested load and charging the storage at time step 3. At time step 8, the requested loads are fulfilled by importing from community and the DER production.

4.6.4 Global Cost Savings Performance

To show that F-DREV minimizes the global cost with the customized trading prices for each community, the global cost savings performance is discussed with three schemes under two scenarios of DER production capacity. The global cost ratios to F-DREV are listed in Table 4.4. Comparing the F-DREV to DREV scheme, F-DREV achieves a lower global cost due to the distinction of different participation levels, where customers select different electricity usage and trading choices according to their customized trading prices. F-DREV is able to reduce the cost 5.4% and 14% more than DREV in scenario 1 (low DER production capacity) and scenario 2 (high DER production capacity). While no community is formed to fully coordinate and perform the trading among customers in IM scheme, the global cost ratios to F-DREV are larger in IM than in DREV. IM requires the cost 6.7% and 18% more than F-DREV under scenario 1 and scenario 2. The achievable performance is stable as the number of customer increases, and is promising with the growing DER production capacity.

4.6.5 Fairness Performance and Effect of P^u, P^l

Fairness performance is evaluated with 500 customers under scenario 2 (high DER production capacity) with IM, DREV, and two F-DREV schemes with two cases of P^u

and P^l. Customers are clustered into 2 groups with the sorted fairness index, where customers in group 1 have higher participation levels than customers in group 2. The summation of the individual cost for each group in the four comparison schemes are presented in Fig. 4.7. Comparing the aggregate costs in group 1 and group 2, without the distinction between different participation levels from customers, the difference between these two groups is not obvious in IM and DREV scheme. There are no incentives for customers to increase their participate level. On the other hand, F-DREV maintains the proposed fairness by letting customers in group 1 (higher fairness indexes) achieve lower individual costs than other customers in group 2.

The degree of distinguishing different participation levels among customers depends on the difference of P^u and P^l. Two cases of P^u and P^l, mentioned in section 4.6.1, are used to show their effect to the fairness performance in F-DREV. As shown in Fig. 4.7, as the difference between P^u and P^l decreases (i.e., P^u, P^l case 2), the difference of the aggregate cost between the two groups also decreases while the global cost increases. However, the global cost in F-DREV is still smaller than the cost in IM and DREV. Depending on the value of P^u and P^l, the individual costs in F-DREV for customers with smaller participation level (group 2) can be slightly higher or lower than their costs in DREV scheme, and are always less than their cost in IM scheme. A trade-off exists between the global cost and the degree of distinguishing different participation levels. It affects the individual cost for customers in group 2, and is a useful reference for service providers to design the value of P^u and P^l in their service plans. Although incentive for customers with lower fairness indexes (group 2) involving F-DREV depends on the difference of agreed P^u and P^l, the fairness index will be updated in every operation period (K time steps). Customers with lower fairness indexes could obtain higher fairness indexes in the future operation periods. Attractions of reducing individual cost can be expected by customers in the long term even if the individual cost for customers in group 2 is slightly higher in F-DREV than DREV. With the proposed fairness, customers have

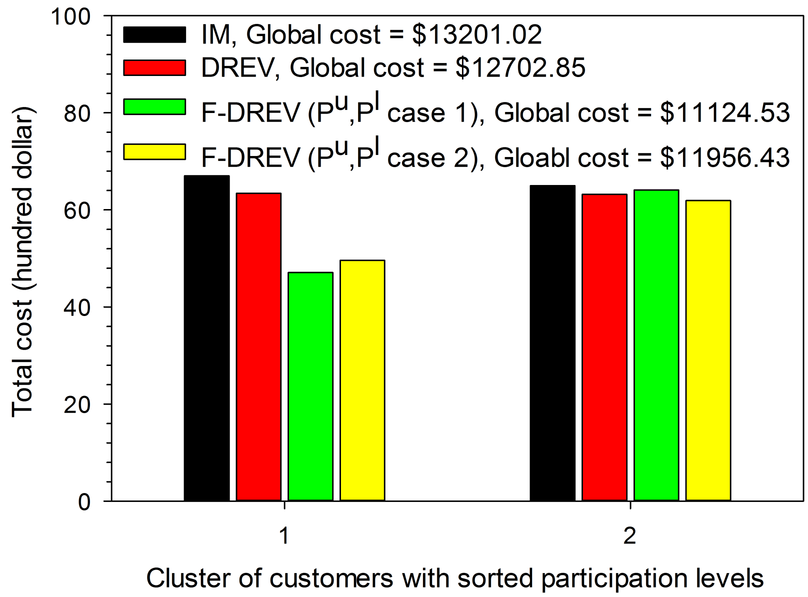

Figure 4.7: fairness performance and effect of P^u, P^l

the incentives to not only use the F-DREV service, but also increase their participation level actively by equipping more DERs or adjusting the flexibility of their requested loads.

4.6.6 Performance of Smoothing Fluctuations

To evaluate F-DREV's ability to constrain the fluctuated penetration within the community, an experiment is conducted in 500 customers under scenario 2 by comparing IM and F-DREV with three different assigned T^u and T^l as shown in Table 4.5. The value of maximum and minimum amount of total requested loads from power grid over 24 time steps, the peak to average ratio (PAR), and the global cost for the four compared schemes are summarized in Table 4.5. The details of the requested energy from the power grid at each time step are presented in Fig. 4.8. As expected, F-DREV restricts the total requested loads from power grid with the determined T^u and T^l, and achieves lower global cost and lower PAR value than IM scheme. With the ability of smoothing the fluctuations, components within the community can be operated grid-friendly. A

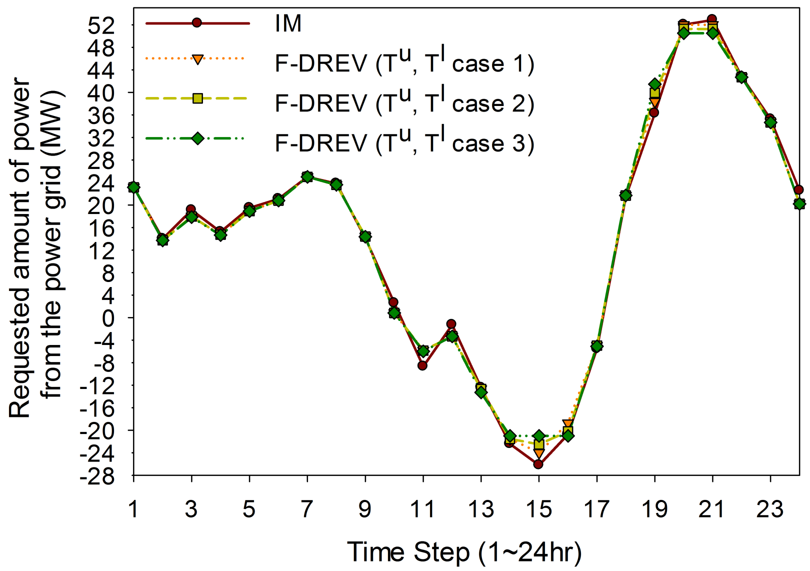

Figure 4.8: Total requested energy from the power grid

Table 4.5: Performance of smoothing fluctuations

	IM	F-DREV case 1	F-DREV case 2	F-DREV case 3
T^u (kWh)	Nan	52000	51250	50500
T^l (kWh)	Nan	-24000	-22500	-21000
Max (kWh)	52861.61	52000	51250	50500
Min (kWh)	-26186	-24000	-24000	-24000
PAR	3.69	3.63	3.58	3.52
Global cost ($)	13201.02	11134.63	11149.45	11171.59

trade-off exists as the increased global cost when assigning the smaller difference between T^u and T^l. The revealed trade-off can be used as reference for F-DREV providers to determine the proper boundary (T^u, T^l) with local utilities in commitments.

4.6.7 Effect of Storage

The effect of storage in F-DREV is discussed with an experiment for 500 customers under both scenarios of DER production capacities. Based on the announcement from tesla that multiple home batteries can be installed together [64], up to 90 kWh for the

Table 4.6: Effect of storage

	Scenario 1			Scenario 2		
S^{max}	IM	DREV	F-DREV	IM	DREV	F-DREV
0 kWh	1.05	1.04	1.00	1.13	1.11	1.00
10 kWh	1.07	1.05	1.00	1.19	1.14	1.00
90 kWh	1.16	1.11	1.00	1.53	1.32	1.00

Table 4.7: Effect of electric vehicle

	Scenario 1			Scenario 2		
Customer types	IM	DREV	F-DREV	IM	DREV	F-DREV
All type 1	1.074	1.065	1	1.204	1.145	1
All type 2	1.069	1.054	1	1.186	1.140	1
All type 3	1.065	1.054	1	1.178	1.140	1

10 kWh battery, we compare three maximum capacity of storages: no storage (0 kWh), single home battery (10 kWh), and multiple home batteries (90 kWh). The global cost ratios to F-DREV scheme are listed in Table 4.6. Without any storage, F-DREV is still able to achieve the smallest global cost in the comparison schemes under both scenarios. When the capacities of involved storages become larger, the global cost can be reduced more. With the foreseeable growth and development in the storage and battery [67], the achievable savings can be expected.

4.6.8 Effect of Electric Vehicle

To discuss the effect of electric vehicle, an experiment is conducted with the 500 customers under both scenarios of DER production capacities. We compare the communities that are formed by all type 1, type 2 and type 3 customers (in Table 4.1) respectively. The global cost ratios to F-DREV scheme are listed in Table 4.7. With the similar behavior of EV loads to interruptible loads, when more electric vehicles are involved in the community, more flexibility can be provided from customers' requested loads. Moreover, when EV has the V2G ability, it can be operated as a storage unit with specific connecting time and requirement. F-DREV is able to reduce the global cost more when more EVs with V2G ability are involved in the community.

4.6.9 Execution Time Performance

To estimate the computation time of executing F-DREV in modern cloud computing platform, a publicly accessible Linux server equipped 40 cores and 252 GB memory under low load is used in this experiment. This server's scale of resources is comparable to most provided instances from Amazon Elastic Compute Cloud [44]. The computation time for 500 customers is 9.28 seconds, and is 20.52 seconds for 1000 customers. For a larger size of community, such as 1500, the computation time is 32.5 seconds. It is significantly smaller than the day-ahead period (24 hrs), and is sufficient for the adjustment interval (following the 5 minutes real-time economic dispatch process) in checking and adjusting processes [30].

4.7 Conclusion

In this chapter, a fair demand response with electric vehicles (F-DREV) is proposed for the cloud based energy management service. Communities are formed by involved customers owning various combinations of EV, DER, storage and multiple loads (fixed, interruptible and non-interruptible). For each community, incentive is maximized as the global cost is minimized by F-DREV for customers controlling their electricity consumption patterns, and the fluctuation is smoothed to operate EVs and DERs grid-friendly. Electricity usage choices and trading choices are combined and determined optimally for each customer via a binary linear programming model. Fairness is proposed as "customers with higher participation level can reduce their individual cost more than those with lower participation level within the same community". It is attainable by customizing trading prices for each customer base on the fairness index. With the proposed fairness, customers are also encouraged to actively increase their participation level by equipping more DERs or adjusting the flexibility of their requested loads.

CHAPTER 5. DISTRIBUTED LARGE-SCALE INTERACTION AND ADJUSTMENT FOR THE CLOUD-BASED ENERGY MANAGEMENT SERVICE

5.1 Abstract

Customers' participations are one of the key factors to demand response and demand side management programs, especially when customers become prosumers. Incentives have to deliver to prosumers to increase their engagements with the energy management for operating their distributed energy resources and electricity loads grid-friendly. In this chapter, the cross-community interaction (XCI) is proposed for the cloud-based energy management service to minimize the global costs as maximizing the incentives for customers within all the collaborated communities over the given time period. The XCI is performed in the distributed fashion to overcome the privacy issue, and the ability, scalability, and efficiency for handling the large-scale data by the various allocated computing resources. It can be solved efficiently via the alternating direction method of multipliers. The mathematic models for XCI are formulated. A cross-community adjustment is also introduced for enhancing XCI under the uncertainty. Performances are evaluated in experiments.

5.2 Nomenclature

Parameters:

G DER production capacity.

T^c Assigned capacity for power distribution line.

P^b Price for buying energy from power grid to community.

P^s Price for selling produced renewable energy from community to power grid.

P^r Price for trading within each community.

D Summation of the requested fix loads.

ηc Charging efficiency for storage.

ηd Discharging efficiency for storage.

γs (Dis)charging rate of storage.

T^u Upper bound for smoothing the fluctuation.

T^l Lower bound for smoothing the fluctuation.

Subscripts:

m m_{th} community.

i i_{th} customer.

j j_{th} interruptible or non-interruptible load.

t t_{th} time step.

z z_{th} power distribution line.

Sets:

$\mathbb{O}$ For the involved community.

$\mathbb{N}$ For customers within each community.

$\mathbb{T}$ For time step, from 1 to t^e.

$\mathbb{Z}$ For power distribution lines.

$\mathbb{L}$ For customers connected to the same power distribution line.

Choice variables for DER:

E^{rc} Export produced energy from DER to community.

E^{rm} Export produced energy from DER to power grid.

E^{rs} Export produced energy from DER to storage.

E^{rd} Export produced energy from DER for load usage.

Choice variables for storage:

I^{ms} Import energy from power grid to storage.

I^{cs} Import energy from community to storage.

I^{rs} Import energy from DER to storage.

E^{sm} Export energy from storage to power grid.

E^{sc} Export energy from storage to community.

E^{sd} Export energy from storage for load usage.

S State of charge for storage.

Choice variables for loads:

I^{md} Use the energy from power grid.

I^{cd} Use the energy from community grid.

I^{rd} Use the energy from DER.

I^{sd} Use the energy from storage.

5.3 Introduction

The active consumers' participations are listed as one of the most important characteristics of a Smart Grid [68], [69]. Especially customers have transformed from consumer to *prosumers* by adopting distributed energy resources (DERs), how to engage customers with the proper management while encouraging the investment of DERs to promote the environment-friendly power grid becomes a critical and important mission. Besides, the widely discussed Demand Response (DR) and Demand Side Management (DSM) programs rely on customers' engagements as the opportunities are provided for customers changing and managing their *"electrical usage choice"*, that is adjusting their consumption pattern according to the fluctuate electricity prices. Thus, how to provide incentives to customers for encouraging them to involve the energy management is an important issue.

In recent years, attentions have been aroused on the customers' engagement and behaviors [70], [71], [72], and varieties of DR and DSM programs [73] have been developed for providing incentives to utilities and customers in literatures. Authors in [52] proposed the DR schemes via formulated games, authors in [74] introduced the sparse load shifting in DSM as a distributed game, and authors in [75] applied the Stackelberg game among multiple utility companies and consumers. The automated residential DR is discussed in [76], and the DSM's impact on residential electricity demand from 30 Swiss utilities is estimated in [77]. However, different from the cloud-based framework, difficulties exist in above literatures as the requirements of deploying the dedicated control entity and implementing the corresponding control mechanisms repeatedly for adopting by various utilities and customers. Along with the literatures in DR and DSM programs, net metering [2] are broadly mentioned to realize the trading between customers and utilities, but only few retail electricity providers [12] provide the excess generation buy-back program, such as the Green Mountain Energy in Texas. The incentives for customers' engagements are still insufficient as the trading choices are limited for prosumers. If prosumers can collaborate to each other, their global costs can be reduced as the increased incentives via the trading among each other.

To handle the above-mentioned difficulties and limitations, our previous work [30] proposed an extensive cloud-based framework to provide customer-oriented Energy Management as a Service (EMaaS) for *"community"*, which is formed by prosumers who agree to involve in the same EMaaS plan. The EMaaS plan is provided by the EMaaS providers and is similar to the existing energy service plan provided by REP. A new price indicator appears when the community is formed and is agreed among all the customers and utilized for customers performing the *"virtual trading"* within the community. This trading is virtual as the physical two-way power distribution line might not exist among customers, and it can be realized efficiently through a mapping mechanism on the cloud-based framework. EMaaS successfully provides the incentives to customers to involve the energy management and also enhance the renewable energy integration. With EMaaS, customers have the opportunity to form as the virtual REPs, and have more *"trading choices"*. Infrastructure costs are significantly reduced and the efficiency, reliability, and scalability are increased. The choices of electricity usage and trading are combined to realize the fair DR with EV on the cloud-based energy management in [78]. Although our previous two works have managed the significant amount of variables, yet the discussed managements were targeted within the same community. Similar to the collaboration among prosumers within the same community, multiple communities should be able to cooperate with others (e.g., trade the surplus/wanting produced renewable energy) to achieve the lower global costs as the additional incentives to all the served prosumers.

The cross-community interaction (XCI) is developed for the cloud-based energy management service to realize the interactions among communities and is the focus of this chapter.

However, the development of XCI for multiple communities, which are served by various EMaaS providers, would bring some critical issues caused by the large-scale data and the different EMaaS providers. The first issue is the privacy concern that prevents the availability of gathering all the data from different EMaaS providers. The second issue is the ability, scalability, and efficiency for handling the large-scale data by the allocated cloud computing resources. To overcome these issues, the XCI is developed in the distributed fashion, where each community achieves the optimal energy management individually in parallel. The characteristic of the distributed XCI is similar to the sharing problem [79] and can be efficiently solved by alternating direction method of multipliers (ADMM) [80]. The ADMM has been popularly used in various areas such as machine learning, data mining [81], and has been successfully applied to various power system tasks. Authors in [82] formulated the optimal power scheduling as an ADMM problem. The paper [83] and [84] proposed the ADMM based algorithm and the N-block ADMM for the robust power system state estimation. [85] proposed the EV charging ADMM framework to perform the optimal fleet charging. A distributed demand response strategy with EV was proposed in [79]. [86] proposed the decentralized economic dispatch using ADMM, and authors in [87] adopted the ADMM for the multi-agent optimization problem. Unlike the discussions in above literatures, the ADMM model of the distributed XCI is more complicated due to the variety choices among customers and various communities.

Moreover, the overwhelmed exchanged data and computations among multiple communities under uncertainty would occur if no proper adjustment designed for the XCI since each community could frequently rerun the EMaaS according to the adjusting process [30]. Instead of formulating the uncertainty into the optimization model like authors in [88] who casted the stochastic problem into coupled ADMM problems, and authors in [79] used the randomness on ADMM for the uncertainty of base load and distributed generator, we proposed the cross-community adjustment (XCA) as the aggregated sliding windows, and can be simply adopted by the XCI.

This chapter proposed the distributed cross-community interaction (XCI) for the cloud-based energy management [30]. The global costs, which include the cost of electricity and environment, are minimized as the incentives are maximized to customers not only within the same community but also in all the collaborated communities. The distributed XCI overcomes the privacy concern and the ability, scalability, and efficiency for handling the large-scale data by the allocated computing resources. It is a collaborated business model for prosumers in the distributed power system. Depending on the different cloud service providers utilized by the EMaaS providers, the distributed XCI for the cloud-based energy management is performed either on the inter-cloud or the intra-cloud level [89], where the communication time in these two levels is small [90]. The XCA is also proposed in this chapter to enhance the efficiency of XCI under uncertainty, that is to avoid the overwhelmed exchanged data and computations.

The contributions of this chapter are summarized in below. (i) This work demonstrates the advantages of EMaaS where the virtual trading can be performed via the collaboration not only among customers but also communities. The XCI is proposed for the cloud-based energy management service to minimize the global costs as maximizing incentives to customers within all the cooperated communities over the given time period. (ii) XCI is developed in the distributed fashion to overcome the privacy concern and the ability, scalability and efficiency for handling the large-scale data by the allocated computing resources. The XCA is also proposed to enhance XCI under uncertainty. (iii) A centralized linear programming model and the distributed ADMM model are formulated. Performances are evaluated with different experiments.

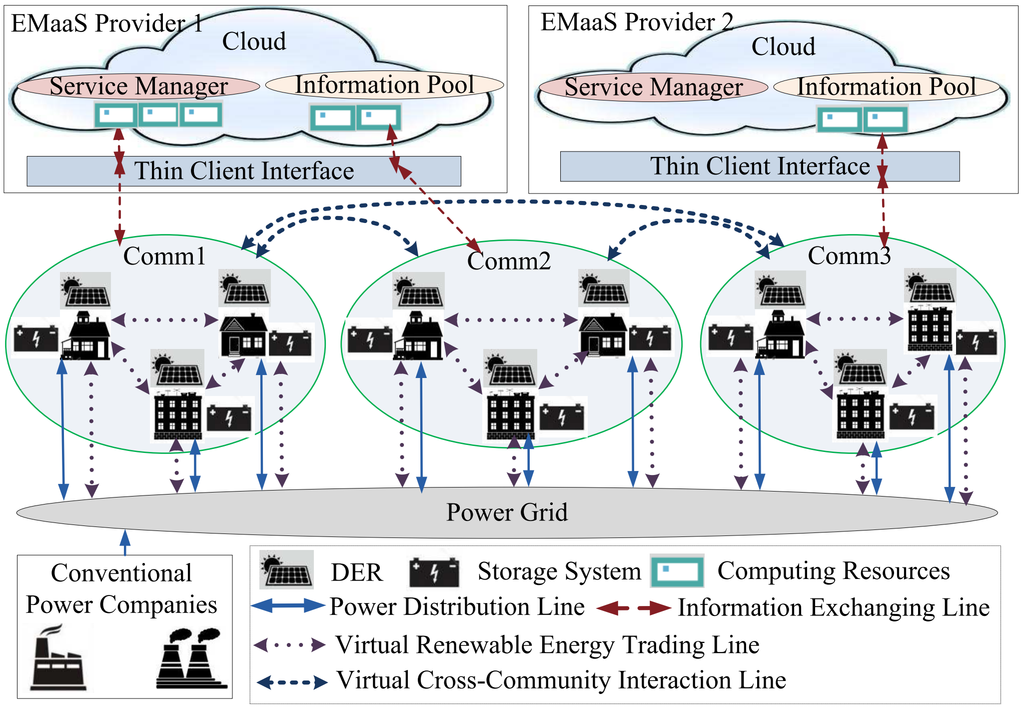

Figure 5.1: Extended Framework for the energy management with cross-community interaction

The remainder of this chapter is organized as follows: the system model is introduced in Section 5.4. Formulations are presented in Section 5.5. Performance evaluation is discussed in Section 5.6, and conclusions are summarized in Section 5.7.

5.4 System Model

This work realized the XCI for the cloud-based energy management service and extends the system model from [30]. The extended framework is firstly introduced in the following subsection. Then, the procedure and the model for the single community are presented. Last, the XCI model is illustrated. For the simplification, the discussed number of multiple communities is set to three, which are indicated as $\{comm1, comm2, comm3\}$ in the set $\mathbb{O}$ throughout the chapter.

5.4.1 Extended Framework

The extended framework for the cloud-based energy management with XCI is illustrated in Fig. 5.1. It is constructed by multiple EMaaS service providers, a power grid, conventional power companies, and multiple communities form by multiple customers. Different EMaaS providers operate the energy management on the cloud with different allocated computing resources and provide various service plans to communities via the thin client interfaces, e.g. web browsers or application programming interface (API). These service plans are similar to the various plans provided by existing REPs, where customers can choose to join by agreeing on the requirements in contract to each EMaaS providers. Each customer represents as various sizes of households and forms the community with other customers who also choose the same service plan. The virtual trading is performed within each community in the dot lines, and across multiple communities with the dash lines.

The power grid is supplied by conventional power companies and the DERs within each community that following the interconnection agreement with local electric transmission and distribution utilities [37]. Customers are assumed to own a small-scale non-dispatchable DER and a storage system in this work. Each DER has a set of choices variables $\{E^{rc}, E^{rm}, E^{rs}, E^{rd}\}$, and various production capacity G. The storage system is able to be powered by both DERs and the conventional generators with the (dis)charging efficiency rate $\{\eta c, \eta d\}$, and has the maximum/minimum storage capacity $\{S^{max}, S^{min}\}$. Each storage system is assumed can be store and release energy quickly, and has a set of choice variables $\{I^{ms}, I^{cs}, I^{rs}, E^{sm}, E^{sc}, E^{sd}\}$.

5.4.2 Procedure for Single Community

The procedure for the single community is shown in Fig. 5.2. The EMaaS provider gathers the K time steps ahead data on the cloud, which includes $\{G, T^c, P^b, P^s, P^r, D\}$ and all the parameters of each storage system. They are the know inputs for the EMaaS,

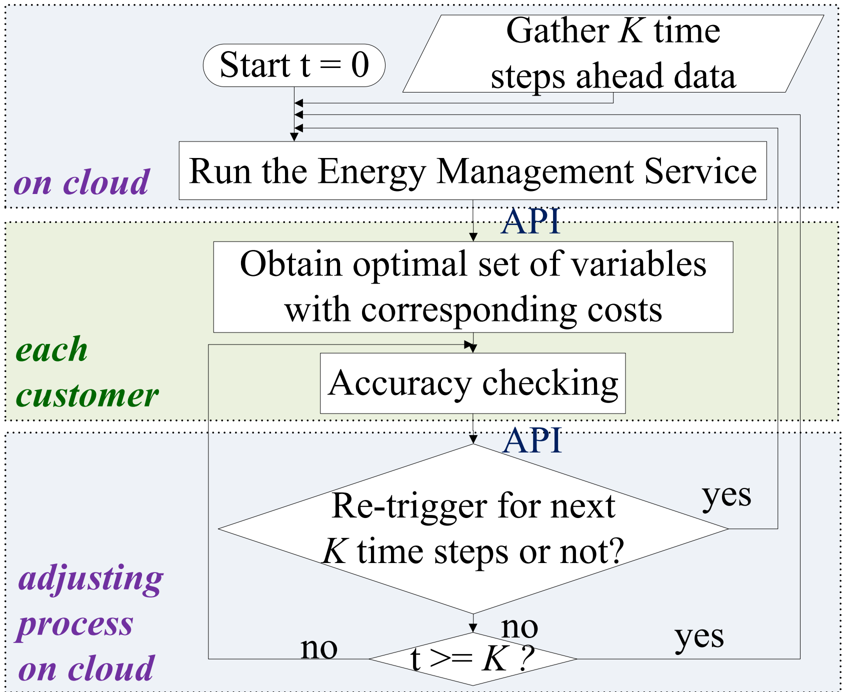

Figure 5.2: Procedure for single community

and can be acquired via forecast technics (G, P^b, P^s), customers' input (D, parameters of the storage system), and the agreed contracts (P^r, T^c). P^b is the price for customer buying the energy that is generated by the conventional power companies from the power grid. P^s is the price for customers selling the produced renewable energy back to the power grid, and it is a smaller value than P^b as the environment cost (i.e., CO_2 emission cost or tax saving provided by the government) is excluded. P^r is the price for customers trading to other within the same community. It is appeared and agreed by all the customers involved in the same service plan. The relationships among these three prices are written in (5.1) and (5.2). T^c is the assigned capacity for each power distribution line by local utilities and depends on the physical distribution network that supports both customers and non-customers of EMaaS.

$$P^s = \alpha P^b, \qquad 0 < \alpha < 1 \tag{5.1}$$

$$P^r = \beta P^b, \qquad \alpha < \beta < 1 \tag{5.2}$$

With all these K time steps ahead data, the EMaaS service provider runs the energy management on the cloud, and provides the optimal set of variables with the corresponding cost as suggestions to each customer via API. The mapping mechanism is used to realized the virtual trading within the community, where customers follow the mapped amount to (dis)charge their storage system in (5.3) and send the energy request in (5.4) to the power grid.

$$Map^s_{i,t} = I^{cs}_{i,t} - \eta d^s E^{sc}_{i,t} - \eta d^s E^{sm}_{i,t}, \forall i \in \mathbb{N}, \forall t \in \mathbb{T} \tag{5.3}$$

$$Map^d_{i,t} = I^{md}_{i,t} + I^{cd}_{i,t} + I^{ms}_{i,t} + I^{cs}_{i,t} - E^{rm}_{i,t} - E^{rc}_{i,t} - \eta d^s E^{sc}_{i,t} - \eta d^s E^{sm}_{i,t}, \forall i \in \mathbb{N}, \forall t \in \mathbb{T}. \tag{5.4}$$

The accuracy checking, and the adjusting process part in Fig. 5.2 are proposed to manage the uncertainties (e.g., sudden electricity usage changes or the operations not following the suggestions) and the forecast errors. The accuracy checking part informs the real-time variance to the adjusting process, and the adjusting process determines to re-trigger the next K time steps ahead management or not. As adopting from our previous work, the complete information can be found in [30].

5.4.3 Model for Single Community

The energy management for the single community can be extended from [30] and formulated as a linear programming model with the 14 choice variables and a state variable S for each customer at each time step. The objective function $f(x)$ for each community is minimizing the electricity cost over K time steps, as shown in (5.5). It is the summation of each customers' cost of fulfilling the demands ($Cost^d$), trading within the community ($Cost^r$), and managing the storage system ($Cost^s$).

$$\min f(x) = \sum_{t \in \mathbb{T}} (\sum_{i \in \mathbb{N}} (Cost^d_{i,t} + Cost^r_{i,t} + Cost^s_{i,t})) \tag{5.5}$$

$$Cost^d_{i,t} = I^{md}_{i,t} P^b_t + I^{cd}_{i,t} P^{rb}_{i,t} \tag{5.6}$$

$$Cost^r_{i,t} = -E^{rm}_{i,t}P^s_t - E^{rc}_{i,t}P^{rs}_{i,t} \tag{5.7}$$

$$Cost^s_{i,t} = I^{ms}_{i,t}P^b_t + I^{cs}_{i,t}P^{rb}_{i,t} - \eta d^s(E^{sm}_{i,t}P^s_t + E^{sc}_{i,t}P^{rs}_{i,t}) \tag{5.8}$$

The objective function is subjected to the several constraints, where (5.9) ensures the customer's demand can be satisfied, and (5.10) guarantees the mapped electricity requests in (5.4) from customers located on the same z_{th} power distribution line won't exceed the assigned capacity.

$$D_{i,t} = I^{md}_{i,t} + I^{cd}_{i,t} + I^{rd}_{i,t} + I^{sd}_{i,t}, \forall i, \forall t. \tag{5.9}$$

$$\sum_{i \in \mathbb{L}_z} Map^d_{i,t} \leq T^c_{z,t}, \forall z, \forall t. \tag{5.10}$$

Constraint (5.11) prevents the exported amount of energy from each DER exceed its production capacity, and (5.12) forbids customer from exporting more than the imported amount of energy from the community. The total available energy for trading within the community is tracked in (5.13) to avert customers from requesting more than the available amount.

$$G_{i,t} = E^{rm}_{i,t} + E^{rc}_{i,t} + E^{rs}_{i,t} + E^{rd}_{i,t}, \forall i, \forall t. \tag{5.11}$$

$$E^{rc}_{i,t} - I^{cd}_{i,t} - I^{cs}_{i,t} \leq 0, \forall i, \forall t. \tag{5.12}$$

$$\sum_{i \in \mathbb{N}} \eta d^s E^{sc}_{i,t} - I^{cs}_{i,t} + E^{rc}_{i,t} - I^{cd}_{i,t} = 0, \forall t. \tag{5.13}$$

For the storage system, (5.14) indicates its status depends on the previous status and the variables at the current time step. Constraints (5.15) and (5.16) ensure the storage is operated in its maximum and minimum capacity after exporting energy at every time steps. Constraint (5.17) is similar to (5.12) to prevent the storage exporting the energy to the community more than the imported amount. The (dis)charging rate and the efficiency constrain the variables in (5.18)-(5.19).

$$S_{i,t+1} = S_{i,t} + \eta c^s \times (I^{ms}_{i,t} + I^{cs}_{i,t} + I^{rs}_{i,t}) - (E^{sm}_{i,t} + E^{sc}_{i,t} + E^{sd}_{i,t}), \forall i, \forall t. \tag{5.14}$$

$$S^{min}_i \leq S_{i,t} \leq S^{max}_i, \forall i, \forall t. \tag{5.15}$$

$$S_{i,t} - E^{sm}_{i,t} - E^{sc}_{i,t} - E^{sd}_{i,t} \geq S^{min}_i, \forall i, \forall t. \tag{5.16}$$

$$\sum_{t'=1}^{t-1} (\eta^{sc} I^{rs}_{i,t'} + \eta^{sc} I^{cs}_{i,t'} - E^{sc}_{i,t'}) - E^{sc}_{i,t} \geq 0, \forall i, \forall t. \tag{5.17}$$

$$\eta c^e \times (I^{ms}_{i,t} + I^{cs}_{i,t} + I^{rs}_{i,t}) \leq \gamma^s_i, \forall i, \forall t. \tag{5.18}$$

$$\eta d^e \times (E^{sm}_{i,t} + E^{sc}_{i,t} + E^{sd}_{i,t}) \leq \gamma^s_i, \forall i, \forall t. \tag{5.19}$$

Constraints (5.20)-(5.22) indicate the corresponding variables for internal behavior changing have to be matched. Constraint (5.23) bound the total imported amount of energy from the power grid with T^u and T^l. These two parameters are utilized to smooth the fluctuation within the community and are agreed between EMaaS provider and the local utility.

$$I^{rd}_{i,t} - E^{rd}_{i,t} = 0, \forall i, \forall t. \tag{5.20}$$

$$I^{rs}_{i,t} - E^{rs}_{i,t} = 0, \forall i, \forall t. \tag{5.21}$$

$$I^{sd}_{i,t} - \eta d^s_i E^{sd}_{i,t} = 0, \forall i, \forall t. \tag{5.22}$$

$$T^l_t \leq \sum_{i \in \mathbb{N}} \{I^{md}_{i,t} + I^{ms}_{i,t} - E^{rm}_{i,t} - \eta d^s E^{sm}_{i,t}\} \leq T^u_t, \forall t. \tag{5.23}$$

The above linear programming model can be rewritten in the matrix format, where all the maintained variables within each community appear as a vector set $\boldsymbol{x}$, where the size of each element of $\boldsymbol{x}$ is n^x that represents every customers' 15 variables at each time step. That is, $\boldsymbol{x} = [\boldsymbol{x}_1, \boldsymbol{x}_2, \cdots, \boldsymbol{x}_{t^e}]$, and each element is maintained with the order of variables in (5.24) from the first customer to the last customer within the community.

$$\begin{aligned} \boldsymbol{x}_1 =& [[I^{md}_{i,t}, I^{ms}_{i,t}, E^{rm}_{i,t}, E^{sm}_{i,t}, I^{cd}_{i,t}, I^{rd}_{i,t}, I^{sd}_{i,t}, E^{rc}_{i,t}, E^{rs}_{i,t}, E^{rd}_{i,t}, I^{cs}_{i,t}, I^{rs}_{i,t} \\ &, E^{sc}_{i,t}, E^{sd}_{i,t}, S]_{i=1}, [\dots]_{i=2}, \cdots]_{t=1,\forall i} \end{aligned} \tag{5.24}$$

The objective function for each community in (5.5)-(5.8) can be represented as (5.25), where $\boldsymbol{Obj}$ is the objective matrix indicating the constant coefficients in (5.6)-(5.8). The equality constraints (5.9), (5.11), (5.13), (5.14), and (5.20)-(5.22) are also rewritten as

Table 5.1: Presentation of z for 3 involved communities

Variables	Interaction behaviors	Constrains
z^1	*comm*1 buy from*comm*2; *comm*2 sell to *comm*1	$\leq l_1$
z^2	*comm*1 buy from*comm*3 *comm*3 sell to *comm*1	$\leq l_2$
z^3	*comm*2 buy from*comm*1 *comm*1 sell to *comm*2	$\leq l_1$
z^4	*comm*2 buy from*comm*3 *comm*3 sell to *comm*2	$\leq l_3$
z^5	*comm*3 buy from*comm*1 *comm*1 sell to *comm*3	$\leq l_2$
z^6	*comm*3 buy from*comm*2 *comm*2 sell to *comm*3	$\leq l_3$

$\boldsymbol{P}^{eq}$ and $\boldsymbol{beq}$ in (5.27). Likewise, the rest inequality constraints are transformed as $\boldsymbol{P}^{ieq}$ and $\boldsymbol{b}$ in (5.26).

$$\min f(\boldsymbol{x}) = \boldsymbol{Obj} \times \boldsymbol{x} \tag{5.25}$$

subject to

$$\boldsymbol{P}^{ieq}\boldsymbol{x} \geq \boldsymbol{b} \tag{5.26}$$

$$\boldsymbol{P}^{eq}\boldsymbol{x} = \boldsymbol{beq} \tag{5.27}$$

5.4.4 Cross-community Interaction

In this chapter, a vector $\boldsymbol{z}$ is introduced to interpret the trading behaviors between the involved communities. Each element in the vector $\boldsymbol{z}$ represents as two corresponding behaviors between any two of the communities. The size of $\boldsymbol{z}$, n^z, depends on the number of the involved communities (n^c), that is $n^c \times (n^c - 1)$. In other words, with the discussed number of involved community is three in this chapter, thus the size of $\boldsymbol{z}$ is 6 (i.e., $z^1, \cdots, z^6$), and the presented behaviors can be found in detail in Table 5.1.

Another objective function $g(\boldsymbol{z})$ is formed by the XCI to further reduce the cost of each community (i.e., the objective function in (5.5)). To be more detail, the corresponded community that buys from the other one can reduce the cost with the trading amount times its purchasing price from the main power grid, P^b. Likewise, the corresponded community that sells to the other one can increase the cost with the trading amount times its selling price to the main power grid, P^s. (5.28) itemizes the objective function $g(\boldsymbol{z})$ with every element in $\boldsymbol{z}$.

$$g(\boldsymbol{z}) = (P^s_{comm2} - P^b_{comm1})z^1 + (P^s_{comm3} - P^b_{comm1})z^2 + (P^s_{comm1} - P^b_{comm2})z^3 + (P^s_{comm3} - P^b_{comm2})z^4 + (P^s_{comm1} - P^b_{comm3})z^5 + (P^s_{comm2} - P^b_{comm3})z^6 \tag{5.28}$$

Each element of $\boldsymbol{z}$ is constrained by the corresponding community's exporting/importing amount to/from the main power grid, that is $(E^{rm} + E^{sm})$ and $(I^{md} + I^{ms})$. These constraints are listed in (5.29)-(5.40). Each element also constrained by the assigned available line capacity between every two communities. The corresponding constraints are listed in the last column Table 5.1, where $\{l_1, l_2, l_3\}$ denote the available line capacity between $(comm1, comm2)$, $(comm1, comm3)$ and $(comm2, comm3)$ respectively.

$$z^1 \leq E^{rm}_{comm2} + E^{sm}_{comm2} \tag{5.29}$$

$$z^1 \leq I^{md}_{comm1} + I^{ms}_{comm1} \tag{5.30}$$

$$z^2 \leq E^{rm}_{comm3} + E^{sm}_{comm3} \tag{5.31}$$

$$z^2 \leq I^{md}_{comm1} + I^{ms}_{comm1} \tag{5.32}$$

$$z^3 \leq E^{rm}_{comm1} + E^{sm}_{comm1} \tag{5.33}$$

$$z^3 \leq I^{md}_{comm2} + I^{ms}_{comm2} \tag{5.34}$$

$$z^4 \leq E^{rm}_{comm3} + E^{sm}_{comm3} \tag{5.35}$$

$$z^4 \leq I^{md}_{comm2} + I^{ms}_{comm2} \tag{5.36}$$

$$z^5 \leq E^{rm}_{comm1} + E^{sm}_{comm1} \tag{5.37}$$

$$z^5 \leq I^{md}_{comm3} + I^{ms}_{comm3} \tag{5.38}$$

$$z^6 \leq E^{rm}_{comm2} + E^{sm}_{comm2} \tag{5.39}$$

$$z^6 \leq I^{md}_{comm3} + I^{ms}_{comm3} \tag{5.40}$$

Grouping constraints (5.29)-(5.40) by each community and the affected element of $\boldsymbol{z}$, they can be rewritten along with the vector $\boldsymbol{x}$ in (5.41) for each community in each time step. Likewise, the constraints for the available line capacity in Table 5.1 can be written in (5.42).

$$\boldsymbol{A}\boldsymbol{x} \geq \boldsymbol{D}\boldsymbol{z} \tag{5.41}$$

$$\mathbb{1}\boldsymbol{z} \leq \boldsymbol{l} \tag{5.42}$$

For readers' convenience, the matrix of $\boldsymbol{A}_t$ and $\boldsymbol{D}_t$ for *comm*1 in the first time step are extracted in below. The first two rows in $\boldsymbol{A}_t$ indicate (5.30) and (5.32). The third and fifth rows represent (5.33) and (5.37). The non-zero elements in $\boldsymbol{D}$ indicate the affected element of $\boldsymbol{z}$ by community 1, that is z^1,z^2,z^3, and z^5.

$$\boldsymbol{A}_t = \begin{bmatrix} 1 & 1 & 0 & 0 & 0 & \cdots & 0 \\ 1 & 1 & 0 & 0 & 0 & \cdots & 0 \\ 0 & 0 & 1 & 1 & 0 & \cdots & 0 \\ 0 & 0 & 0 & 0 & 0 & \cdots & 0 \\ 0 & 0 & 1 & 1 & 0 & \cdots & 0 \\ 0 & 0 & 0 & 0 & 0 & \cdots & 0 \end{bmatrix}_{n^z \times n^x}$$

$$\boldsymbol{D}_t = \begin{bmatrix} 1 & 1 & 1 & 0 & 1 & 0 \end{bmatrix}_{1 \times n^z}$$

The matrix $\boldsymbol{A}$ and $\boldsymbol{D}$ in (5.41) are composed by the $\boldsymbol{A}_t$ and $\boldsymbol{D}_t$ for every time steps.

$$\boldsymbol{A^T} = \begin{bmatrix} \boldsymbol{A}_{t=1}, \boldsymbol{A}_{t=2} \cdots \boldsymbol{A}_{t=t^e} \end{bmatrix}$$

$$\boldsymbol{D^T} = \begin{bmatrix} \boldsymbol{D}_{t=1}, \boldsymbol{D}_{t=2}, \cdots \boldsymbol{D}_{t=t^e} \end{bmatrix}$$

5.5 Formulation

5.5.1 Centralized

Following the discussion in subsection 5.4.3 and 5.4.4, the energy management service with the XCI can be formulated as a centralized optimization problem. The object function in (5.43) subjects to the constraint (5.42), and the constraints (5.26), (5.27), (5.41) for every involved community, which are represented as (5.44) - (5.46).

$$\min_{\boldsymbol{x}_m, \boldsymbol{z}} \sum_{m \in \mathbb{O}} f_m(\boldsymbol{x}_m) + g(\boldsymbol{z}) \tag{5.43}$$

subject to: (5.42), and

$$\boldsymbol{A}_m \boldsymbol{x}_m \geq \boldsymbol{D}_m \boldsymbol{z}, \forall m \in \mathbb{O} \tag{5.44}$$

$$\boldsymbol{P}_m^{ieq} \boldsymbol{x}_m \geq \boldsymbol{b}_m, \forall m \in \mathbb{O} \tag{5.45}$$

$$\boldsymbol{P}_m^{eq} \boldsymbol{x}_m = \boldsymbol{beq}_m, \forall m \in \mathbb{O} \tag{5.46}$$

5.5.2 Distributed

It is inefficient to solve the problem (5.43) in a centralized way due to the massive variables and the constraints. In addition, different communities might be severed by different energy management service providers, which leads to the privacy issues for customers, and brings the difficulty to perform the energy management altogether by gathering different parts of data together. The objective function in (5.43) is the standard sharing problem [79] and can be efficiently solved by the big data optimization algorithm. In this work, the alternating direction of multiplier method (ADMM) [80] is utilized. The approaches of transforming the centralized problem (5.43) to the distributed ADMM format are discussed in detail in below.

To perform the problem in the distributed approach, the global variable $\boldsymbol{z}$ in the objective function (5.43) has to be decoupled as $\boldsymbol{z}_{\boldsymbol{m}}$ for each community. The objective function can be represented as (5.47). Constraint (5.49) is designed to ensure the decoupled $\boldsymbol{z_m}$ achieve the same global variable $\boldsymbol{\phi}$, where the indicated matrix $\boldsymbol{C}_m$ for the related $\boldsymbol{z_m}$ within each community.

$$\min_{\boldsymbol{x}_m,\boldsymbol{z}_m} \sum_{m\in\mathbb{O}} \{f_m(\boldsymbol{x}_m) + g(\boldsymbol{z}_m)\} \tag{5.47}$$

subject to: (5.42), (5.45), (5.46), and

$$\boldsymbol{A}_m\boldsymbol{x}_m = \boldsymbol{D}_m\mathbf{z}_m + \boldsymbol{Y}_m, \forall m \in \mathbb{O} \tag{5.48}$$

$$\boldsymbol{z}_m = \boldsymbol{C}_m\boldsymbol{\phi}, \forall m \in \mathbb{O} \tag{5.49}$$

As the variable vectors, $\boldsymbol{x}$ and $\boldsymbol{z}$ are maintained by each community for every time steps from $t = 1 \cdots t^c$, they can be grouped as another variable vector $\boldsymbol{X}$.

$$\boldsymbol{X}^{\boldsymbol{T}} = \left[\boldsymbol{x}_{t=1}, \boldsymbol{z}_{t=1}, \cdots, \boldsymbol{x}_{t=t^e}, \boldsymbol{z}_{t=t^e}\right]$$

With the variable vector $\boldsymbol{X}$, the equations (5.47)-(5.49) can be simplified to (5.50)-(5.52). Constraints (5.42), (5.45) and (5.46) also have to transform to (5.53) and (5.54), where the prior two inequality constraints are combined. Finally, our problem (5.47) is modeled in the ADMM format as presented in below.

$$\min_{\boldsymbol{X}_m,\boldsymbol{Y}_m,\boldsymbol{\phi}} \sum_{m\in\mathbb{O}} \theta(\boldsymbol{X}_m) \tag{5.50}$$

subject to:

$$\boldsymbol{A}_m\boldsymbol{X}_m - \boldsymbol{Y}_m = \mathbf{0}, \forall m \in \mathbb{O} \tag{5.51}$$

$$\boldsymbol{B}_m\boldsymbol{X}_m - \boldsymbol{C}_m\boldsymbol{\phi} = \mathbf{0}, \forall m \in \mathbb{O} \tag{5.52}$$

$$\boldsymbol{Gc}_m^{ieq}\boldsymbol{X}_m \geq \boldsymbol{Gb}_m, \forall m \in \mathbb{O} \tag{5.53}$$

$$\boldsymbol{Gc}_m^{eq}\boldsymbol{X}_m \geq \boldsymbol{Gbeq}_m, \forall m \in \mathbb{O} \tag{5.54}$$

where $\boldsymbol{B}_m$ is the matrix with the zeros matrix with the size of in front and an identity matrix following the size of each z_m for every time step t.

$$\boldsymbol{B}_m = \left[[\mathbf{0} \quad \mathbb{1}]_{t=1} \ldots [\mathbf{0} \quad \mathbb{1}]_{t=t^e}\right]$$

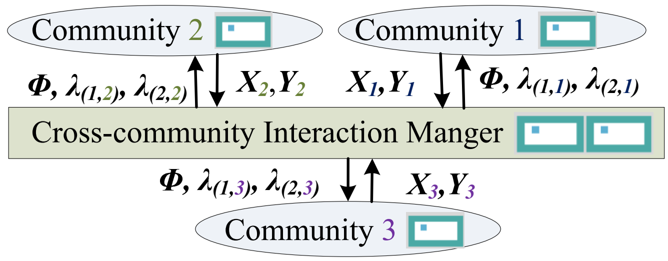

Figure 5.3: Conceptual diagram for ADMM steps

5.5.3 ADMM Steps

The problem (5.50) is multi-block ADMM, and can be efficiently solved iteratively [80][91] with its augmented lagrangian ($\mathcal{L}$) in (5.55), where $\{\boldsymbol{\lambda}_{(1,m)}, \boldsymbol{\lambda}_{(2,m)}\}$ are the dual variables, $\{\rho_1, \rho_2\}$ are the penalty parameters, and $\langle \cdot \rangle$ denotes the inner product.

$$\mathcal{L}(\boldsymbol{X}_m, \boldsymbol{Y}_m, \boldsymbol{\phi}, \boldsymbol{\lambda}_{(1,m)}, \boldsymbol{\lambda}_{(2,m)}) = \sum_{m \in \mathbb{O}} \theta(X_m) + \frac{\rho_1}{2} \sum_{m \in \mathbb{O}} ||\boldsymbol{A}_m \boldsymbol{X}_m - \boldsymbol{Y}_m||^2$$
$$+ \langle \boldsymbol{A}_m \boldsymbol{X}_m - \boldsymbol{Y}_m, \boldsymbol{\lambda}_{(1,m)} \rangle + \frac{\rho_2}{2} \sum_{m \in \mathbb{O}} ||\boldsymbol{B}_m \boldsymbol{X}_m - \boldsymbol{C}_m \boldsymbol{\phi}||^2 + \langle \boldsymbol{B}_m \boldsymbol{X}_m - \boldsymbol{C}_m \boldsymbol{\phi}, \boldsymbol{\lambda}_{(2,m)} \rangle \tag{5.55}$$

Variables $\{\boldsymbol{X}_m, \boldsymbol{Y}_m, \boldsymbol{\phi}, \boldsymbol{\lambda}_{(1,m)}, \boldsymbol{\lambda}_{(2,m)}\}$ are updated on the different cloud computing resources following the (5.56)-(5.60), where the superscript k indicated the iteration number. Sequentially, community m update the owned X_m^k following the (5.56), which subjects the constraint (5.53) and (5.54), and Y_m^k with the closed form solution in (5.57) on the cloud computing resources that are utilized by individual community respectively. Then each community's cloud computing resources send the updated X_m^{k+1} and Y_m^{k+1} to the main energy management controller's cloud computing resources to further update the global variable ϕ^k, the dual variables $\lambda_{(1,m)}^k$, and $\lambda_{(2,m)}^k$ following (5.58)-(5.60). After the update, variables $\phi^{k+1}, \lambda_{(1,m)}^{k+1}, \lambda_{(2,m)}^{k+1}$ are sent to the computing resources that are maintained by each community. This procedure is illustrated in Fig. 5.3, and the algorithm is addressed in details for our five-block ADMM problem in Algorithm 1.

$$\boldsymbol{X}_m^{k+1} = \operatorname{argmin}_{\boldsymbol{X}_m}\{\theta(\boldsymbol{X}_m^k) + \frac{\rho_1}{2}||\boldsymbol{A}_m\boldsymbol{X}_m^k - \boldsymbol{Y}_m^k||^2 + \langle \boldsymbol{A}_m\boldsymbol{X}_m^k - \boldsymbol{Y}_m^k, \boldsymbol{\lambda}_{(1,m)}^k\rangle$$

$$+ \frac{\rho_2}{2}||\boldsymbol{B}_m\boldsymbol{X}_m^k - \boldsymbol{C}_m\boldsymbol{\phi}^k||^2 + \langle \boldsymbol{B}_m\boldsymbol{X}_m^k - \boldsymbol{C}_m\boldsymbol{\phi}^k, \boldsymbol{\lambda}_{(2,m)}^k\rangle\} \tag{5.56}$$

$$\boldsymbol{Y}_m^{k+1} = \frac{1}{\rho_1^2}(\rho_1\boldsymbol{A}_m\boldsymbol{X}_m^{k+1} + \boldsymbol{\lambda}_{(1,m)}^k) \tag{5.57}$$

$$\boldsymbol{\phi}^{k+1} = \operatorname{argmin}_{\boldsymbol{\phi}_i}\{\sum_{m\in\mathbb{O}}\theta(\boldsymbol{X}_m^{k+1}) + \frac{\rho_2}{2}\sum_{m\in\mathbb{O}}||\boldsymbol{B}_m\boldsymbol{X}_m^{k+1} - \boldsymbol{C}_m\boldsymbol{\phi}^k||^2$$

$$+ \langle \boldsymbol{B}_m\boldsymbol{X}_m^k - \boldsymbol{C}_m\boldsymbol{\phi}^k, \boldsymbol{\lambda}_{(2,m)}^k\rangle\} \tag{5.58}$$

$$\boldsymbol{\lambda}_{(1,m)}^{k+1} = \boldsymbol{\lambda}_{(1,m)}^k + \rho_1(\boldsymbol{A}_m\boldsymbol{X}_m^{k+1} - \boldsymbol{Y}_m^{k+1}) \tag{5.59}$$

$$\boldsymbol{\lambda}_{(2,m)}^{k+1} = \boldsymbol{\lambda}_{(2,m)}^k + \rho_2(\boldsymbol{B}_m\boldsymbol{X}_m^{k+1} - \boldsymbol{C}_m\boldsymbol{\phi}^{k+1}) \tag{5.60}$$

Algorithm 1 ADMM Steps

```
for k = 1 to MAXITER do
    for m ∈ 𝕆 do
        X_m^{k+1} ← (5.56) s.t. (5.53), (5.54)
    end for
    for m ∈ 𝕆 do
        Y_m^{k+1} ← (5.57)
    end for
    φ^{k+1} ← (5.58)
    for m ∈ 𝕆 do
        λ_{(1,m)}^{k+1} ← (5.59)
    end for
    for m ∈ 𝕆 do
        λ_{(2,m)}^{k+1} ← (5.60)
    end for
end for
return {X_m, Y_m, φ, λ_{(1,m)}, λ_{(2,m)}}
```

Convergence Analysis: The convergence of multi-block ADMM has been discussed widely in recently. Sufficient conditions have been established in [91] and [92] for K-block ($K \geq 3$) ADMM. With the linear coupling constraints, our ADMM problem falls into the categorization in [93], where it is guaranteed to converge to the global optimal solution under some regularity assumptions [94].

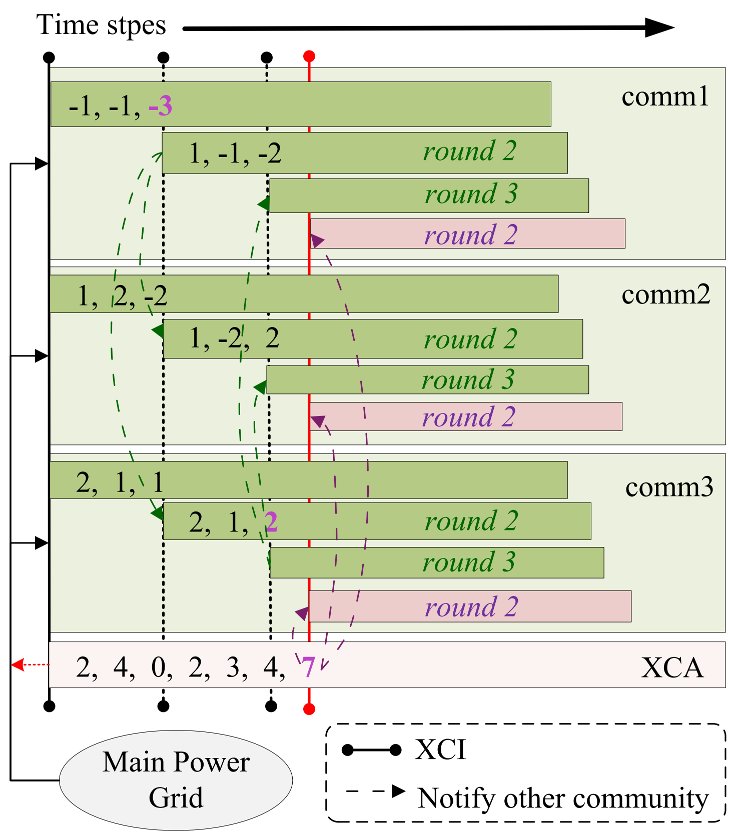

Figure 5.4: Illustration of the Cross-Community Adjustment

5.5.4 Cross-community Adjustment

The adjustment process in Fig. 5.2 is maintained by each community individually. Without proper management scheme, the individual adjustment process in each community might cause the overwhelmed computations and exchanged data. The cross-community adjustment is proposed to collaborate with the communities who physically located on the same electrical distribution line or region. An example is illustrated in Fig. 5.4 with the threshold equals to 5 to determine to re-trigger the next K time step ahed EMaaS. In the beginning, the XCI with EMaaS is performed for these three communities. Without the cross-community adjustment, the inaccurate accumulated error in $comm1$ initiates the adjusting process at $t = 3$ and informs the other two communities to perform the XCI with EMaaS again. Likewise, at $t = 6$, $comm3$ triggers its adjusting process, and rerun the XCI with EMaaS. Massive computations and exchanged data

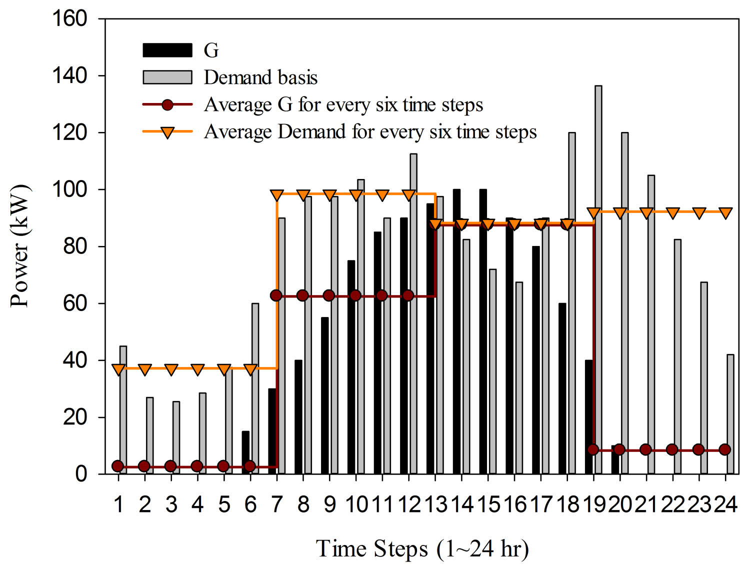

Figure 5.5: Basis of Demand and Renewable Energy Production Capacity

could be avoided with the proposed cross-community adjustment as the uncertainty fluctuation could be complemented among communities. As shown in our example, the XCI with EMaaS only needs to be performed at $t = 6$ with the cross-community adjustment.

5.6 Performance Evaluation

5.6.1 Experiment Environment

The production capacity of each customer's DER follows the basis in Fig. 5.5, according to the hourly day-ahead data from CAISO [61] that solar generations are average work from clock 6 to clock 20 a day during summer. To indicate the different configurations of each DER (i.e., size, angle, the location of shades, etc.,), the basis is multiplied to a uniform distribution, where $\mathcal{U}(0.2, 1.2)$ and $\mathcal{U}(0.8, 1.8)$ are used to show the environments of low and high DER production capacity respectively. The requested demand for each customer is designed based on the typical household load profile in Fig. 5.5. The demand basis times a uniform distribution $\mathcal{U}(0.5, 1.5)$ to mimic the various sizes of households and customers' electricity usage preferences. For the simplification purpose, we represent 24-time steps into 4-time steps, where each step originally stands for an hour becomes 6 hours, and the amount of indicated power becomes the average amount of the original amount within 6 hours. The simplification is indicated with lines in Fig. 5.5.

The discussed storage system follows the spec of Tesla Powerwall, where the $\eta c, \eta d$ are set to 0.95 that match the powerwall's round-trip efficiency, and γs is set to 2 kW [64]. The storage capacity follows [65], where S^{min} is 15% of S^{max}. In this work, the blackout situation is assumed will not occur. Customers are designed to locate on different distribution lines in our experiment, and the available capacity of each power distribution line (T^c) is assigned based on the number of connected customer times the largest requested electricity demand D. As the ability of smoothing the fluctuation within each community has been discussed and demonstrated thoroughly in [30] and [78], this chapter waives this discussion and sets T^u and T^l as the unbounded value.

The prices indicators $\{P^b, P^s\}$ are acquired via the predictions and P^r is agreed in contracts between the joined customers and each EMaaS service providers. To mimic the experiment more realistic, the design of P^b for each community is based on the fuel cost predicted by a conventional generator. The conventional generator support 3000 households includes the involved customers and other households who didn't the energy management service. The utilized quadratic fuel cost function in [41] $a+b(3000\times AvgDe)+c(3000\times AvgDe)^2$ sets the value of P^b falls in the range of 1.4 to 9.8 cents per kWh. The $AvgDe$ is the average of all customers' demands within the community and the coefficients $(a,b,c) = (240, 7, 0.007)$. The α and β in (5.1) and (5.2) are designed as 0.4 and 0.7 respectively. The implementation is conducted in MATLAB and run on the publicly accessible server.

Table 5.2: Advantage of Cross-community Interactions

	low DER production capacity				high DER production capacity			
Customers	50	75	100	125	50	75	100	125
$l = 0$	1.060	1.047	1.039	1.034	1.174	1.118	1.082	1.063
$l = 500$	1.036	1.03	1.024	1.025	1.112	1.079	1.055	1.041
$l = 1000$	1.017	1.015	1.012	1.008	1.054	1.039	1.027	1.021
$l = 1500$	1	1	1	1	1	1	1	1

5.6.2 Cost saving Performance

To show the advantage of XCI for the cloud-based energy management, the cost saving performance is conducted with the experiments under the scenarios of high and low DER production capacity, the cases of $\{50, 75, 100, 125\}$ customers in each community, and the available community line capacities (l) are set as $\{0, 500, 1000, 1500 \text{ kW}\}$, where $l = 0$ is the case without XCI. The results of cost ratio to the case of $l = 1500$ are listed in Table. 5.2. The global cost of three communities with 50 customers in each community under low DER production capacity requires 6% more if no XCI exists among communities. Likewise, without XCI, the global cost of three communities requires 11.8% more for the size of 75 customers under high DER production capacity. The cost saving is larger when the available community line capacity is larger and the DER production capacity is higher. To be more details, the advantage of XCI becomes more significant when the ratio of l to the number of customers within each community is larger.

5.6.3 ADMM Converge Performance

The convergence of ADMM is discussed with the scenario of low DER production capacity, and each community has three customers. The available line capacities (l_1, l_2, l_3) are all set to 100. Fig. 5.6 shows the convergence of the objective value $(hundreddollars/kWh)$ over the iterations with different settings of the penalty parameter (ρ), which is set to equal to ρ_1, and ρ_2. The problem in (5.50) successfully converges regardless the setting of ρ. To further show the difference affects from the various ρ,

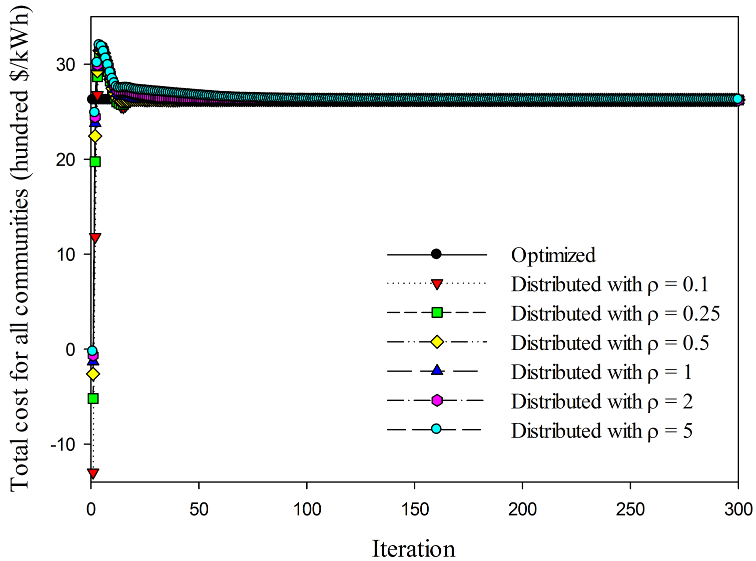

Figure 5.6: Convergence of ADMM

iteration from 25 to 150 are extracted in Fig. 5.7. When the ρ is set to a larger value, the convergence rate is slower.

5.6.4 Advantage of Cross-community adjustment

In order to test the advantage of cross-community adjustment, another program is implemented to mimic the example in Fig. 5.4. Three communities are assumed to connect on the same power distribution line, and the threshold for the individual adjusting process is 5 in each community ($IndiAdj$). Each community is designed to have the inaccurate data from -25 to 25 with the probability of Err at every time step. Once the accumulated inaccurate data exceed the threshold, the communication will be initiated among communities and trigger the ADMM for the next round. That is, the count of communication package (CommPkg#) will +2, and the count of performed ADMM (ADMM#) will +1. The results with three different settings of the cross-community adjustment threshold (i.e., 2.5, 2.75 and 3 times the threshold of the single community as $CrCom1$, $CrCom2$, and $CrCom3$ respectively) are presented in Fig. 5.8, where

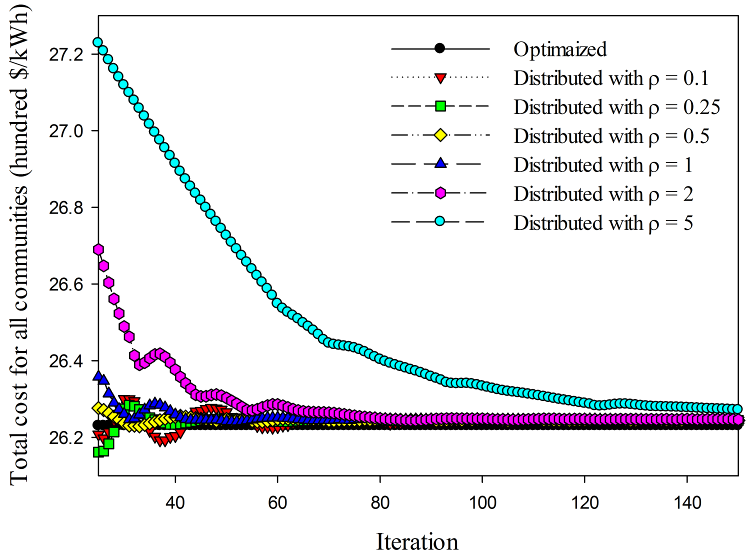

Figure 5.7: Extracted iteration 25 to 150 from Fig. 5.6

the number in x-axis indicates the different Err cases, and the counts in each case are the average of ten experiment runs. The advantage of cross-community adjustment is successfully shown with the increasing difference between the $IndiAdj$ and other three $CrCom$ scenarios; especially the difference becomes more significant when the Err is larger.

5.7 Conclusion

In this chapter, the cross-community interaction (XCI) is proposed for the cloud-based energy management. With the enabled trading choices among all customers within all the collaborated communities, the global costs (includes both environmental cost and electricity cost) can be minimized as the incentives are maximized to customers. The XCI for the cloud-based energy management is formulated in the distributed approach to overcome the privacy concern of maintaining customers information by each community, and the concern of the allocated cloud computing resources' ability, scalability, and efficiency. The XCI for the cloud-based energy management is efficiently solvable via

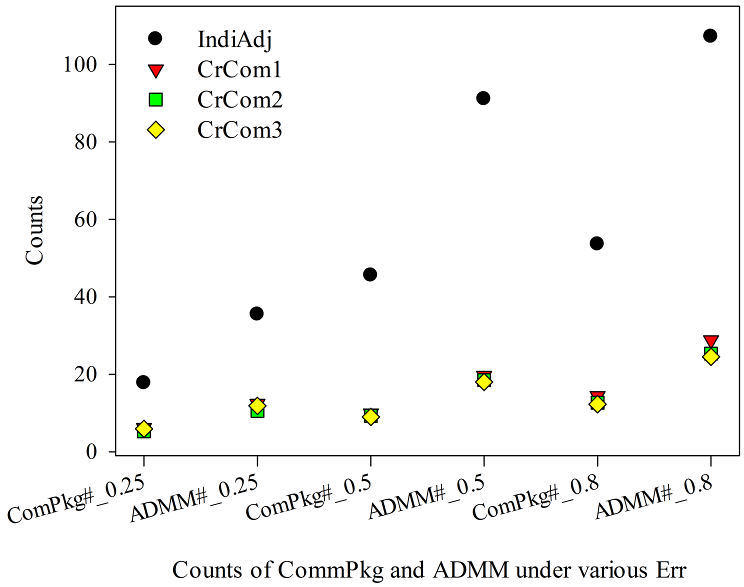

Figure 5.8: Advantage of Cross-community adjustment

alternating direction method of multiplier. The communication time for the distributed XCI is small as it is utilized by different cloud computing resources from different EMaaS providers in the inter-cloud or the intra-cloud level. The cross-community adjustment is also proposed to enhance the efficiency of XCI for EMaaS under uncertainty by reducing the unnecessarily overwhelmed data exchanging and computations.

CHAPTER 6. SUMMARY AND FUTURE WORK

6.1 Summary

As the discussed introduction in chapter 1, the extensive cloud-based framework is proposed to provide Energy Management as a Service (EMaaS) in chapter 2. It provides the opportunity for prosumers forming the community as the virtual retail electricity provider (REP) to perform the virtual trading and achieve the lower global costs (includes the cost of electricity and environment) over the given time. With the formed community, distributed energy resources are managed together to enhance the renewable energy integration.

The fair demand response with electric vehicle (F-DREV) is proposed for the cloud-based energy management service in chapter 3. Customers with the electric vehicle, distributed energy resource, storage and multiple loads form the community and obtain the optimal choices (electricity usage and trading) from F-DREV. To attract customer to actively participate, the trading prices are customized for customers to attain the proposed fairness, which is "customers with higher participation level can reduce their individual cost more than those with lower participation level within the same community."

Chapter 4 proposed the distributed large-scale cross-community interaction and adjustment for the cloud-based energy management to allow communities collaborated to each other. The global costs are minimized to customers within all the cooperated communities over the given time period. To overcome the privacy concern and the ability, scalability, and efficiency for handling the large-scale data by the allocated computing resources, the cross-community interaction (XCI) is developed in the distributed fashion, where each community achieves the optimal energy management individually in parallel. XCI for the cloud-based energy management can be efficiently solved by alternating direction method of multipliers. The cross-community adjustment is also proposed to enhance the XCI under uncertainty. The centralized linear programming model and the distributed ADMM model are formulated.

6.2 Future Work

While this thesis has proposed the extensive cloud-based framework to provide the EMaaS and realized the F-DREV and XCI for the cloud-based energy management service, the future work of this these could generally fall into two directions. That is the investigation of customers' behaviors and the realizations for the cloud-based energy management service. As variety choices have created to prosumers, how would these choices be further utilized to achieve the smart grid functions would be an interesting aspect. For example, whether if the changing of prosumers' behavior will lead to the self-healing, how to adopt the uncertainty other than the sliding windows discussed in chapter 4, and how will the business model in the cloud-based energy management affect the distributed electricity marketing and wholesale electricity marketing. The other direction is the realizations for the cloud-based energy management service, for example, how to extend the distributed large-scale energy management in chapter 4 with the utilization of big data analysis and machine learning techniques. Also, with the discussed fairness in chapter 3, the categorization of customers would be an important factor to affect the fairness indexes. Customers with similar criteria, i.e., the invested DER and the average requested electricity demand, should be assigned to the same community to maintain the proposed fairness properly, and this would become a clustering problem.

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