Uncertainty-Aware Transactive Operation Decisions for Grid-Friendly Building Clusters

BY

Yang Chen

B.S., Henan Polytechnic University, 2010
M.S., Chongqing University, 2013

THESIS

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Defense Committee:

Mengqi Hu, Chair and Advisor, Mechanical and Industrial Engineering
Michael J. Scott, Mechanical and Industrial Engineering
Houshang Darabi, Mechanical and Industrial Engineering
Lin Li, Mechanical and Industrial Engineering
Zhi Zhou, Argonne National Laboratory

This thesis is dedicated to my family, my love and the memory of my grandparents.

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SUMMARY

Chapter 1 introduces the basic statistics of energy consumption in U.S. It is indicated by recent years' data from Department of Energy that building sector consumes more energy than any other sectors. To improve building energy efficiency, capability of integrating distributed energy resources has transformed building from traditional consumer into prosumer that could interact with power grid via two-way communication of 'smart grid'&'smart building' technology. Motivated by potential of transactive operation of building with power grid, electric vehicle and other buildings, this research focus on 'efficient transactive control of grid-friendly building clusters at distribution level'.

In *Chapter 2*, the fundamental incentives for buildings to be clustered is clarified. Previous research has indicated the collective benefits of building clusters, however, whether every participated building could benefit from clustered operation has been neglected. Therefore, this chapter investigates individual contribution and gain during the collaboration from the perspective of individual buildings, the possibility of ensuring relative and absolute fairness during benefit distribution is revealed by our proposed analytical models. Possible energy transaction price is also suggested.

Chapter 3 focuses on large scale transactive operation of building clusters. Although various distributed decision frameworks have been developed for energy system operation, most of existing distributed implementations have relative complex structures and could not realize parallel autonomous operation. To make distributed parallel decisions and protect sensitive information for building agents, we propose a bi-level energy transaction framework, where building agents operate their own energy systems driven by transactive decisions made by distribution system operator. The proposed framework and algorithm are first evaluated on small-scale building-charging station transaction, then tested on large scale building clusters consisted of up to 256 buildings.

Chapter 4 deals with transactive operation of building clusters under uncertainties. Scenario based stochastic programming is adopted to model uncertainties from electricity load and solar radiation. In this chapter, except purchasing and buying electricity from electricity market, building's potential in ancillary service market is also modeled by providing different kinds of operating reserves from power generating unit and electric storage of buildings. To decrease the problem complexity, scenarios are trimmed by reduction algorithm and a model predictive control or rolling horizon control approach is also embedded in the proposed distributed stochastic transaction process to make online decisions.

Chapter 5 summarizes the main contributions of this thesis, and points out other extended application areas that our proposed distributed decision framework could be applied on. Possible issues and improvements for current research are also put forward for future study.

CHAPTER 1

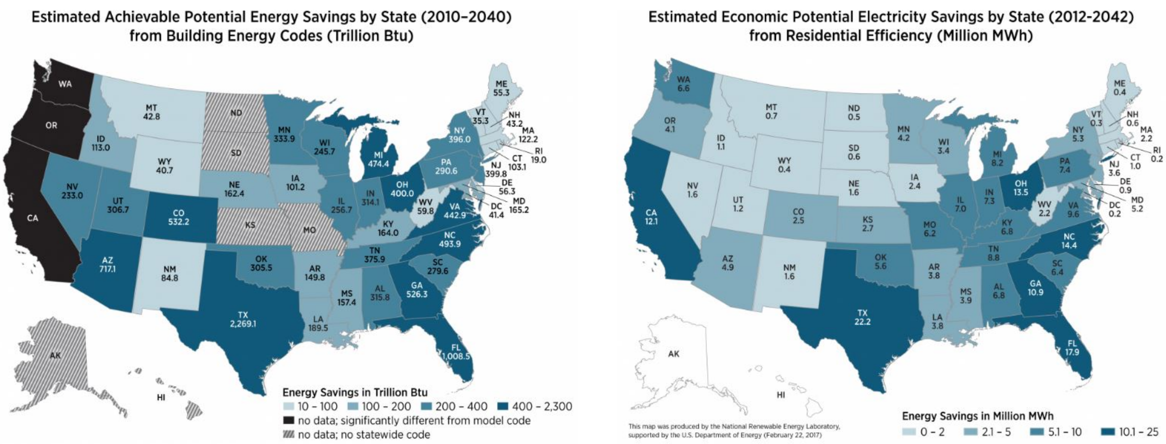
INTRODUCTION

Primary energy consumption of the United States in 2016 has a slight increase from 2015 level, totaled 97.4 quadrillion British thermal Units (Btu) (127). From the perspective of energy sources, fossil fuels made up 81% of the total consumption in 2016, slightly lower than 2015 levels, but down from 86% in 2005. Coal consumption decreased by 9%, nearly offsetting increases in consumption of renewables, petroleum, natural gas, and nuclear fuel. Petroleum consumption increased to 19.6 million barrels per day in 2016, led by increases in transportation sector. Natural gas consumption increased to 27.5 trillion cubic feet, led by higher demand in electric power and industrial sectors while it fell slightly in residential and commercial building sectors, reflecting lower heating demand. On the other side, among all the main energy consumption sectors, the building sector is responsible for more than 40% of U.S. primary energy consumption since 2010, which is about 44% more than transportation sector and 36% more than industrial sector in the U.S., it also accounts for 44% of carbon dioxide (CO2) emissions in U.S. per year, more than any other sector (121).

1.1 Background and Motivation

The building sector plays a critical role in achieving transition to a low-carbon economy. At the UN Framework Convention on Climate Change (Copenhagen, December 2009), more than 100 countries associated themselves with the Copenhagen Accords, which set the objective of holding "the increase in global temperature below two degrees Celsius". This implies reducing global CO2 emissions by 50% by 2050 and buildings must deliver a large part of this reduction (54). To improve energy efficiency of buildings, several efforts have been made in past decades worldwide from more stricter building standard codes, appliance standards, to energy certification polices, for example, in countries of Asia-Pacific Partnership on Clean Development and Climate (APP), building energy standards usually cover insulation, thermal and solar properties of building envelope (walls, roofs, windows and other areas where the interior and exterior of a building interface). Most standards also cover heating, ventilation and air conditioning (HVAC), hot water supply systems, lighting, and electrical power. Some cover additional issues such as use of natural ventilation, renewable energy and building maintenance (34).

Within domestic of U.S., the Building Technologies Office (BTO) of Department of Energy (DOE) supports the development and implementation of residential and commercial building energy codes by engaging with government and industry stakeholders, and by providing technical assistance for code development, adoption, and compliance (122). Through advancing building codes, BTO aims to improve building energy efficiency, and help states achieve maximum savings. For instance, on July 25 2017, DOE issued a preliminary determination that Standard 90.1-2016 would achieve greater energy efficiency in buildings subject to the code. DOE estimates national savings in commercial buildings of approximately 8.2% energy cost savings, 7.9% source energy savings and 6.7% site energy savings (125). In additional, an estimated 75% of U.S. buildings will be new or renovated by 2035, building energy codes could ensure efficient energy usage over the life of the building (122). The estimated potential energy savings by state from building energy codes and estimated potential electricity savings by state from residential efficiency (126) is shown in Figure 1(a) and Figure 1(b).



(a) (b)

Figure 1: (a) Estimated achievable potential energy savings by state from building energy codes, (b) Estimated economic potential electricity savings by state from residential efficiency

Generally, for buildings, the major areas of energy consumption are heating, ventilation, and air conditioning – 35% of total building energy; lighting – 11%; major appliances (water heating, refrigerators and freezers, dryers) – 18% with remaining 36% in miscellaneous areas including electronics (108), see Figure 2. For each component of the building, there are opportunities both from, 1) improving its own energy performance by new technologies, for example, some new emerging technologies about hardware (128): high-efficiency heat pumps that reduce or eliminate the use of refrigerants that can lead to greenhouse gas (GHG) emissions, thin insulating materials, windows and building surfaces with tunable optical properties, high efficiency lighting devices, etc., and 2) improving the way they are controlled as a part of integrated building systems, for example, improved software for optimizing building design and operation (25), low cost energy harvesting sensors and controls, interoperable building communication systems and optimized control strategies, decision science issues affecting purchasing and operating choices.

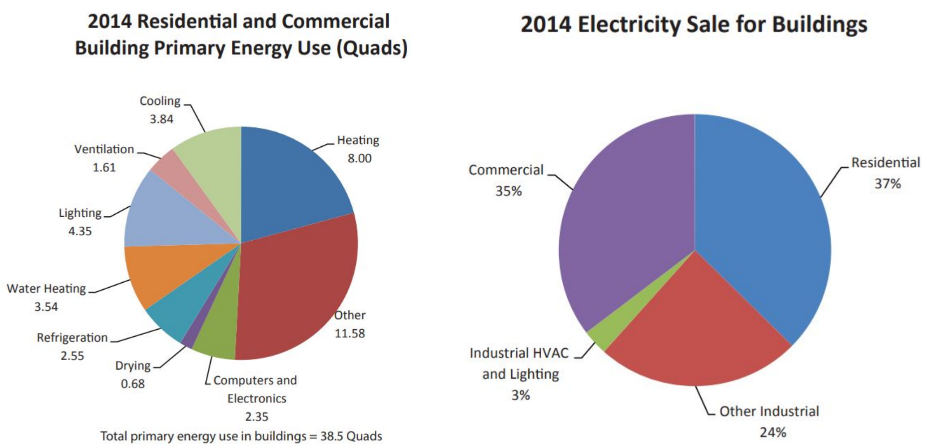


Figure 2: (a) Primary energy usage distribution in residential and commercial buildings, (b) Electricity sale for buildings

Building efficiency must be considered as improving the performance of a complex system designed to provide occupants with a comfortable, safe, and attractive living and work environment. It requires superior architecture and quality construction from design stage and intelligent operations which usually include integration with sophisticated electric power grid (108). For current buildings already built, comparing with higher capital cost investment on efficiency-limited equipments, the cost of installing a smart building energy management system is relatively low. However, electricity delivery in the U.S. depends on an aging and overburden patchwork system, and some parts of the electric grid predate the turn of the 20th century (8). To modernize the grid and make it "smarter", concept of very promising "Smart Grid" technology has been proposed in past few years which make it possible by two-way communication technologies, control systems, and computer processing (124). Through the use of smart grid technologies, operators could reduce power outages, reduce storm impacts, and restore service faster when outages occur. Utilities also benefit from modernized grid, including improved security, reduced peak loads, increased integration of renewables and lower operational costs. Consumers can better manage their own energy consumption profile and respond quickly to market signals, especially for buildings with distributed energy generation sources and smart energy management system (a.k.a., "Smart Building").

Besides "Smart Grid" & "Smart Building" technologies, to unlock the true potential of buildings, another initiative "**Transactive Energy**" is defined by the Gridwise Architecture Council as "a set of economic and control mechanisms that allows the dynamic balance of supply and demand across the entire electrical infrastructure using value as a key operational parameter". It refers to the "combination of economic and control techniques to improve grid reliability and efficiency. These techniques may also be used to optimize operations within a customer's facility" (44)(100)(43).

All of these technologies and initiatives urge the building sector to improve its energy efficiency, have better capabilities for interacting with the power grid, and drive the research moving from a centralized control of individual buildings to collaborative/**transactive control** on a network of smart buildings (a.k.a., building clusters). The transactive control has the following benefits (101): 1) electrical generation and load can be balanced more effectively which can help preserve the grid reliability, 2) critical decision making can be accomplished in a highly parallel and redundant manner to reduce single points of failure as the size of the grid continues to grow, 3) consumers of the power can assess actual, real-time grid information and power values and optimize their power use and local energy generator to accommodate their own preferences, and 4) new distributed generation resources and managed loads can be integrated into the grid more easily, with the impacts managed locally.

1.2 Smart Building Transactive Energy Management

"Buildings, as the largest electricity consumer, should work in synergy with and be responsive to the grid, and be at least grid-friendly to avoid putting additional stress on the balance of power grids. The large load shifting capacity of buildings enables them to be the most effective responsive loads and DR resources. Buildings have great flexibility or elasticity in changing their power demands due to their cooling/heating load shifting potential (besides other nonessential loads) as a result of passive and active thermal storages. The building loads can then be altered in terms of both magnitude and time in response to the needs of power grids. The change of power use (or even power export to grid) in a building might be activated autonomously in response to time-of-use or dynamic electricity pricing, or controlled directly by the grid operator (or third-party)" (132). The true potential of buildings participating in power grid could be fully explored and exploited through the interaction between buildings and power grid (B2G), integration of buildings and electric vehicles (V2B) and aggregation of cooperative building clusters (B2B).

Demand response offers a solution to many of the challenges faced by electricity grids. Commercial buildings are good candidates to DR programs for several reasons: 1) commercial buildings constitute a significant portion of electricity load, 2) commercial buildings have many predictable loads operating on repeating schedules, 3) many commercial buildings have centralized control, reducing the cost for integrating them in DR program (66). Using EnergyPlus, a simulation model of a multi-purpose commercial building was developed and calibrated, then DR strategies are evaluated for a number of building zones, which utilise different heating, cooling and ventilation equipment (21). A day-ahead multi-objective optimization model is proposed (120) for time-of-use (TOU) price based DR program, which integrates distributed electricity generation sources in buildings to optimize the economy and occupants' comfort by synergetic dispatch of source-load-storage. A two-stage optimization framework for price-based DR of commercial buildings is proposed (65) that include variable speed heat pumps (VSHPs). The energy consumption and reserve provision of VSHPs, as well as plug-in electric vehicles, are then co-optimized considering the operating conditions of distribution networks for preand post-contingency states of wind power generation. An innovative probabilistic method for evaluating impact of residential DR choices is proposed (116), which considers uncertainties related to load demand, user preferences, environmental conditions, house thermal behavior and wholesale market trends. Interdisciplinary mechanism that combines machine learning, optimization, and data structure design focus (141) on building a DR and home energy management system that can meet the needs of real life conditions. A novel control algorithm is presented (67) for joint DR management and thermal comfort optimization in micro-grids equipped with renewable energy sources and energy storage units. Effectiveness of the proposed method is validated in a micro-grid composed of three buildings, a PV array, a wind turbine and an energy storage unit.

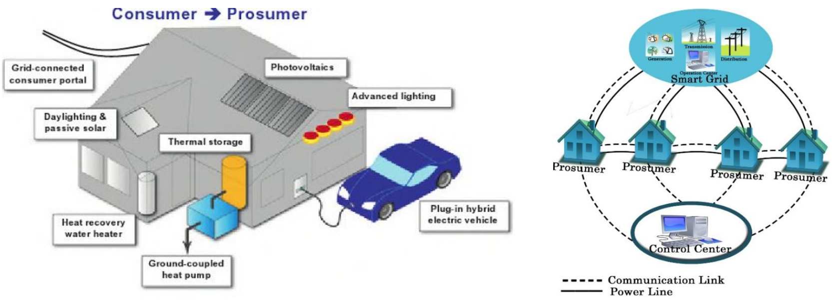
To significantly reduce the energy consumption from the two main sectors, building and transportation, the potential of vehicle-to-building (V2B) integration has attracted greater attention recently. It is demonstrated that the V2B integration can achieve cost savings (39) and CO2 emissions reductions (58) using appropriate operation decision strategy. Instead of installing stationary energy storage system, the EVs can help buildings reduce peak energy demand and energy cost (22). By using the V2B technologies, the benefits for demand side management and outage management can be significantly improved (99)(117). Optimal sizing of workplace charging stations is studied (53) considering probabilistic reactive power support for PHEVs which are powered by solar photovoltaic (PV) units in medium voltage commercial building networks. Charging and discharging process for multiple EVs in a building's garage are studied to optimize energy consumption profile of the building (89). An EV charging algorithm is designed for smart homes/buildings to determine optimal schedules of EV charging based on PV output and electricity consumption (134). The economic impacts of EVs under various demand response strategies for smart households are studied in (32). The grid impact of charging PHEVs in an existing office building is examined in (131). Different charging strategies and charging power ratings are developed to allow a high number of EVs to be charged with a lower grid impact and an increased self-consumption on renewable energy. The potential benefits for V2B integration together with additional revenue through providing ancillary service can be amplified (41). The benefits of optimizing EV and home energy scheduling considering user preferences in a residential community are discussed in (81)(88). For commercial building microgrids that containing EVs and PV system, a heuristic operation strategy, which is based on real-time acquisition data without forecasting of PV output or EV charging demand, is proposed to improve self-consumption of PV energy and reduce the impact of uncoordinated EV charging on power grid (72).

Other than the large body of research on B2G and V2B, another noteworthy effort (B2B) is appeared, which is to form transaction energy network to allow multiple micro-grids sharing and exchanging energy for better energy performance. It is demonstrated that the building level micro-grid clusters are more energy efficient than a single building level micro-grid (49), and the first attempt to make operation decisions for micro-grid clusters is a memetic algorithm based framework (49). The proposed framework is capable of deriving Pareto solutions for micro-grid clusters in a decentralized manner. The high computational cost of memetic algorithm based decision framework prohibits its use for short time scale (e.g., hourly) operation decisions of micro-grid clusters. To this end, a particle swarm optimization based decision framework is proposed in (50) to enable short time scale operation decisions which can significantly improve energy efficiency and achieve more energy cost savings. Other than cost savings, the micro-grid clusters can also improve environmental sustainability, reduce primary energy consumption and enhance micro-grid's resilience capability to power disruptions and extreme events (23). The micro-grid clusters can be self-organized to guarantee energy reliability of critical loads and overall energy efficiency after extreme event which isolates the micro-grid clusters from the main power grid (47). For example, each micro-grid can decide whether to connect to the clusters depending on available generation resources, and negotiate with other micro-grids in the clusters for optimal energy exchange. A hierarchical bi-level decision framework based on the system of systems concept is proposed (60) to enable coordination between micro-grid clusters and distribution grid, and optimally operate micro-grid clusters. A self-organizing map based clustering algorithm is proposed in (56) to group different micro-grids into different clusters based on their energy profiles, and a distributed decision model is proposed to study homogeneous and heterogeneous micro-grid clusters.

1.3 Distribution Level Transactive Market Operation

"The rise of distributed generation and the transformation of the traditional consumer into a prosumer are changing the way the revenue flows in the energy value chain and changing the value chain itself". "The prosumer is an electric customer who generates electricity and sells excess back to the utility. This customer relies on the distribution grid to deliver electricity to the utility in addition to back up services when on-site generation is insufficient to meet host demand". "In the future electricity business model, all parties transact with each other using tenders and transactions that are communicated and recorded on transaction platforms. Transactions are for energy and transport product. The four types of entities in the business model are: 1) Energy service parties own and control all facilities for the usage, production, and storage of energy. A customer, prosumer, DER, and generator are energy service parties, 2) Transport services parties own and control all facilities for transport of energy, distributed operators and transmission operators, 3) Intermediaries provide exchange, market-making, matching, arbitrage, hedging, and financing services, 4) Transaction platform providers furnish transaction platform information processing technology and are not a party to any tenders and transactions or ownership and control of energy and transport facilities" (38). The emerging prosumer and the energy transaction market of building clusters are shown in Figure 3(a) (source:(38)) and Figure 3(b) (source:(106)). Correspondingly, the research focus has transferred from seeking optimal operation strategy of individual building to coordinated operation among multiple interconnected buildings.

"Along with more and more technologies available to customers (e.g. buildings), the energy distribution system are getting more and more complicated comparing with traditional one-way street form faraway generators to electricity customers. After customers have the ability to meet their own energy demands and exporting surplus electricity services to the power grid, the distribution systems also needs a new kind of management with multiple options. First one is an integrated distribution planning process which might need more investment in infrastructures, second one is to transform utilities into a "Distribution System Platform"



(a) (b)

Figure 3: (a) traditional consumer transform to prosumer, (b) prosumer-based energy sharing

provider (DSP) who will look across all options to optimize the distributed system. A third one is to establish an "Independent Distribution System Operator" (IDSO or DSO).

From the perspective of operating mode, DSP and DSO are similar somehow: one entity co-optimizes all available distributed resources, which increases reliability and lowers costs. It is ideally that existing distribution utilities should play this role as the DSPs. However, it may be difficult to set up a regulatory environment that effectively incentivizes the distribution utility to optimize across all possible DERs to find the least-cost, most reliable, cleanest option. One possible regulatory option is true performance-based regulation, where the utility's finances are directly tied to quantitative outcomes in each of those categories. Alternatively, distribution system optimization could be handled by an independent organization.

An Independent DSO would act as an independent market-maker for a diverse number of behind-the-meter participants to buy and sell energy services, and it would not own any physical assets itself. The DSO would optimize distributed energy resources (DERs) like energy efficiency, demand management, demand response, distributed generation, electric vehicle chargers, building management systems, and microgrids. It would provide a market that coordinates and accurately compensates the owners of these DERs for the benefits they provide to the grid, including avoiding alternative investments. By allowing DERs to compete with more traditional energy service providers, the hope is that the least cost resource mix will be uncovered, lowering costs for customers.

Introducing competition and creating a DSO would (1) integrate more DERs on the system; (2) get the most out of existing grid resources; (3) give consumers more choice and control; and (4) spur a more "transactive distribution system where independent agents can trade and combine their services to meet specific customer needs, enabling the emergence of a whole new class of energy market participants. Under the proposed framework, the Distributed System Operator would serve as a system optimizer on the local level, calling on least-cost resources to meet distribution system goals. Those least-cost resources could be provided directly by customers, but it's more likely they would be provided by third-party aggregators (e.g., traditional Energy Service Companies, new kinds of energy service businesses). Individual residential customers are unlikely to ever interact directly with the DSO.

In addition to a local system optimizer, the DSO would also act as an aggregator, bidding this optimized portfolio of resources into the traditional marketplace run by the Independent System Operator or Regional Transmission Organization. So a DSO allows distributed energy resources (DERs) to compete with traditional independent generators for ISO-level services and bilateral energy services contracts. Meanwhile, the distribution utilities would retain ownership of the assets related to distribution, including primary responsibility to maintain and upgrade the system subject to state laws on performance" (7).

1.4 Scope and Organization

As reviewed in Section 1.2, transactive potential of B2G (between building and power grid), B2V (between building and electric vehicle) and B2B (between building and building) has been revealed and studied. However, current research stays at small scale, transactive control at distribution level has not been touched due to missing of large scale transaction architecture and distributed coordination algorithms. Along with rising building prosumers, it's necessary to explore energy transaction at prosumer market.

To bridge these gaps, the reviewed B2B transaction (Section 1.2), especially at large scale, is focused in this research. Decision models and algorithms are developed to study the collaborative decision of building clusters which can minimize the energy consumption and provide possible ancillary services to ensure the reliability of distribution network. The overall research map is described in Figure 4 and the research issues in each phase are in the following discussion.

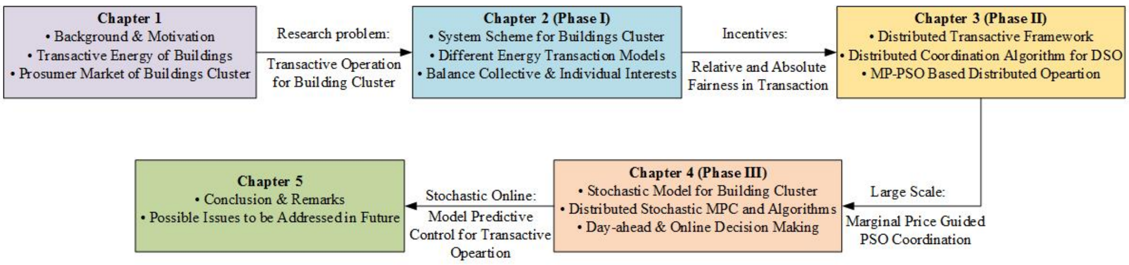


Figure 4: Overall Research Map and Chapter Organization

It is noticed that most of existing literature in energy efficient operation of buildings focuses on energy system operation of single building or a very small scale building cluster (2-4 buildings). With the context of smart grid and transactive energy, the benefits of building clusters to reduce energy consumption and the capabilities of building clusters to provide ancillary service have been discovered very recently. Therefore, studying large scale transactive operation for grid-friendly building clusters is necessary. In order to address this topic thoroughly, three phases are planned and according research issues are proposed:

Phase I. Why do we need to pay more attention about buildings from demand side? Are there enough incentives for individual buildings to be clustered together? And how to achieve the optimal collective benefits while considering the interests for participated individual buildings?

According to recent studies, building clusters can significantly reduce energy cost, improve environmental sustainability and resilience capability to extreme events, most of the studies focus on maximizing the collective interests, such as minimizing energy cost for the building clusters. The individual interests of some buildings cannot be guaranteed. We propose four operation decision models to study the transactive energy management for the building clusters and balance the collective and individual interests (Chapter 2).

Phase II. For a community level application, the challenges are: how to construct an efficient energy transaction framework? How to coordinate the transactive process among buildings in the cluster? And how to protect privacy information in this transactions?

Although various distributed decision frameworks have been developed and applied for energy system operation, most of the existing distributed implementations are not absolutely parallelized or have relatively complex structures such as peer-to-peer structure. It prohibits their applications for large scale building clusters. In addition, the existing distributed decision frameworks require extensive information (e.g., detailed decision models) to be exchanged among different decision agents which is not able to protect the private information of decision agents. To bridge these research gaps, we propose a swarm intelligence based bi-level distributed decision framework to model the energy transactions in the building clusters (Chapter 3).

Phase III. For this phase, we propose to study online transactive operation for building clusters to provide ancillary services and minimize energy consumption. There will be several main challenges here: 1) How to model ancillary services provided by buildings, 2) How to deal with the uncertainties from energy demand and other ambient parameters?, 3) How to make effective online decisions with updated information?

To embrace the uncertainties from electricity load and solar radiation, scenario-based centralized two-stage stochastic operation model is firstly established. Electric storage and Power Generating Unit (PGU) in Combined Cooling, Heating and Power (CCHP) system are assumed to provide different kinds of operating reserves. The proposed swarm intelligence based distributed decision framework and coordination algorithm in Phase II are extended to incorporate with stochastic programming. In order to further decrease model complexity of planning optimization and utilize updated information, a model predictive control (MPC) or rolling horizon control approach is also embedded in the proposed energy transaction process (Chapter 4).

CHAPTER 2

DEVELOP LOCAL PROSUMER MARKET OF BUILDING CLUSTERS*

The emerging technology, transactive energy network, can allow multiple interconnected buildings (a.k.a. building clusters) to exchange energy for greater energy efficiency. Existing research has demonstrated that the building clusters can achieve some collective interests (e.g., minimizing total energy cost). However, some buildings may have to make sacrifices of their individual interests (e.g., increasing cost) for collective interests of the clusters. To bridge these research gaps, we propose four different transactive energy management models for building clusters where each building is allowed to have energy transactions with others. The first model focuses on maximizing collective interests, both the collective and individual interests are considered in the second model, and the last two models aim to maximize both the collective and individual interests. The performances of the proposed models are evaluated using a cluster of sixteen buildings with different energy profiles. It is demonstrated that 1) all of the four models can maximize the collective interests, 2) the third model can maximize the relative individual interests where each building can achieve the same percentage of cost savings as the clusters, and 3) the fourth model can maximize the absolute individual interests where each building can achieve the same amount of cost savings.

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2.1 Energy Transaction among Interconnected Buildings

A typical smart building consists of distributed energy sources (such as power generators, storage system, etc.) and loads, and is able to operate in parallel with, or independently from, the mainpower grid (40). Specifically, smart buildings can utilize both distributed energy generator, such as fuel cell, CCHP system, solar PV, and distributed energy storage, such as electric and thermal storage, to satisfy electric, cooling and heating demand.

The research on individual building or building level micro-grid operation focuses on developing optimal operation strategies for the energy systems (e.g., distributed generator, distributed energy storage) in the building. In general, two different models, such as deterministic and stochastic models, are developed to study the micro-grid operation where the random issues in the micro-grid are ignored in the deterministic models. An economic power dispatch decision model for micro-grid with the objective of minimizing fuel cost during grid-connected operation while ensuring stable operation after islanding (2) shows that a micro-grid can be economically operated during grid-connected mode and operated in a near-optimal way during islanded mode with cost increasing up to 0.7%. A multi-objective mixed integer nonlinear programming model is proposed in Ref. (136) to find optimal operation decisions for a building level micro-grid and enable further analysis of micro-grid under various load conditions. A novel double-layer coordinated control approach for both grid-connected and stand-alone micro-grid energy management is proposed in Ref. (57) where the simulation results for a typical micro-grid show good convergence in either mode. It is demonstrated that the energy supply and demand in a residential micro-grid can be balanced using a three-step methodology in advance planning and real-time control of domestic appliances (84). The stochastic operation decision models are developed to mitigate the impacts of uncertainties to micro-grid operations. The energy scheduling of micro-grid is formulated as MIP (mixed integer programming) problem in Ref. (42) under the practical background of a low energy building where uncertainties in demand and renewable energy sources are considered. A two-stage stochastic programming formulation is proposed in Ref. (80) to study a building where responsive loads (residential, commercial and industrial ones) and distributed generation units are applied to provide reserve for compensating forecast errors of renewable energy, and reserve capacity allocation and optimal battery scheduling are considered. An online optimal energy/power control method based on a MIP model using rolling horizon window is presented (77) for the operation of energy storage in grid-connected micro-grids, and a robust counterpart model is proposed to handle uncertainty in system states prediction with a very modest increase in computational time.

It is demonstrated that the building clusters are more energy efficient than a single building (49), and the first attempt to make operation decisions for building clusters is a memetic algorithm based framework (49). The proposed framework is capable of deriving Pareto solutions for building clusters in a decentralized manner. The high computational cost of memetic algorithm based decision framework prohibits its use for short time scale (e.g., hourly) operation decisions of building clusters. To this end, a particle swarm optimization based decision framework is proposed in Ref. (50) to enable short time scale operation decisions which can significantly improve energy efficiency and achieve more energy cost savings. Other than cost savings, the building clusters can also improve environmental sustainability, reduce primary energy consumption and enhance building's resilience capability to power disruptions and extreme events (23). The micro-grid clusters can be self-organized to guarantee energy reliability of critical loads and overall energy efficiency after extreme event which isolates the micro-grid clusters from the main power grid (47). For example, each micro-grid can decide whether to connect to the clusters depending on available generation resources, and negotiate with other micro-grids in the clusters for optimal energy exchange. A hierarchical bi-level decision framework based on the system of systems concept is proposed (60) to enable coordination between micro-grid clusters and distribution grid, and optimally operate micro-grid clusters.

Although the building clusters can significantly reduce energy cost, improve environmental sustainability and resilience capability to extreme events, most of the existing operation decision models for building clusters focus on maximizing the collective interests, such as minimizing energy cost for the building clusters. The individual interests of some buildings cannot be guaranteed. For example, some buildings maybe more cost expensive if they join the clusters to exchange and trade energy with other buildings. The transformation of building clusters concept will be prohibited without a model to balance the collective and individual interests.

To bridge these research gaps, we propose four operation decision models to study the transactive energy management for the building clusters and balance the collective and individual interests. In this research, the collective interest for the building clusters is to minimize the total energy cost for the clusters, and the individual interest is defined to maximize the relative percentage of cost savings or the absolute amount of cost savings for each building. In our proposed models, each building has its own CCHP, PV, electric and thermal storage to satisfy its electric and thermal loads, and can freely share electric and thermal energy with other buildings. The first model is developed to maximize the collective interests (e.g., minimize total energy cost) only, and the second model is to maximize the collective interests and keep the individual interests (e.g., the percentage of cost savings for each building) at satisfactory levels. The third and fourth models aim to maximize both the collective and individual interests. The individual interest in the third model is defined to maximize the relative percentage of cost savings for each building. We model the price for the local transactive energy in the fourth model, and define the individual interest as maximizing the absolute amount of cost savings for each building. According to the study on a cluster of sixteen buildings, we can conclude that: 1) all of the four models can maximize the collective interests, 2) all the buildings can have the same percentage of cost savings as the building clusters using the third model, and 3) the absolute amount of cost savings can be evenly shared by each building and the local energy transaction price can be determined using the fourth model. It can also be concluded from this research that: 1) the first model is appropriate when all the buildings are operated by one manager, 2) the second model is suitable when the buildings have heterogeneous individual interests, 3) the third and fourth models are preferred when the buildings have homogeneous individual interests and the fourth model is better to the highly cooperative building clusters. In summary, the contributions of this research lie in three aspects: 1) a mathematical decision framework is proposed to study the transactive energy management for the building clusters, 2) the first attempt to develop various models to study the balance between collective and individual interests in various building clusters, and 3) the local energy transaction in the building clusters is modeled and an optimal local energy pricing strategy can be determined using the proposed models.

2.2 System Architecture of the Building Clusters

In this section,we propose a framework to model the building clusters. Based on the modeling framework, a basic operation decision model for the building clusters is discussed in Section 2.2.1.

The modeling framework to study the building clusters with local energy transaction market is shown in Figure 5, each building has three modules: 1) load module which considers electricity, cooling and heating load, 2) generating module which considers solar PV panel and CCHP system, and 3) storage module which considers electric and thermal energy storage. Each building can share and exchange electric and thermal energy with other buildings through a local transaction market. The solid line in Figure 5 represents electricity flow and the dashed line represents thermal energy flow. The PGU (power generation unit) in the CCHP system has a gas turbine as its prime mover to generate electricity and a recovery system to pro- duce heating energy, an auxiliary boiler can convert fuel into heat to compensate the shortage of cooling and heating loads. Power grid is assumed to support electricity purchasing and selling while the local energy market can allow both electricity and thermal energy transactions. Hence, electricity energy storage can be charged by electricity from PV, PGU, power grid and local transaction market, and thermal storage can be charged by thermal energy from PGU, boiler and local transaction market. For each building, its energy load should be satisfied while minimizing its own operation cost.

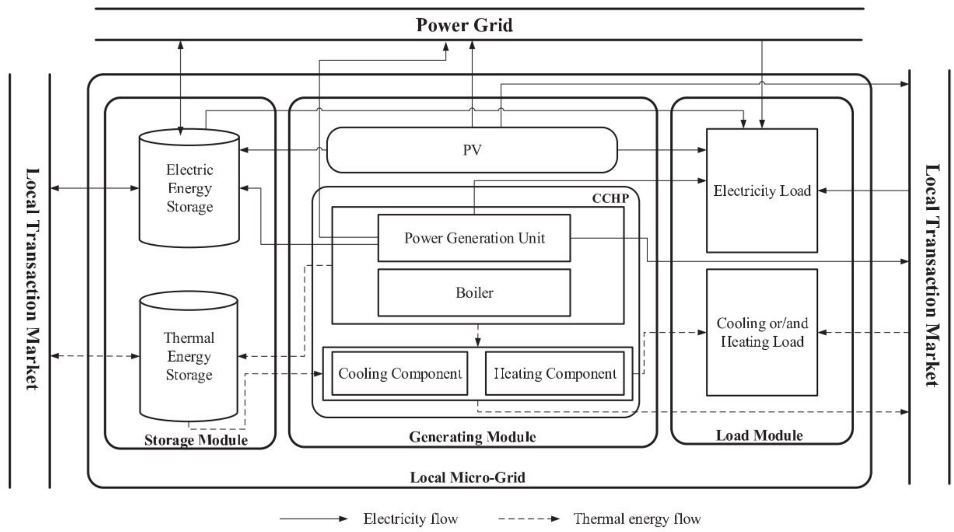


Figure 5: Overall schematic of the building clusters with local energy transaction

2.2.1 Mathematic Model for the Building Clusters

All the variables and parameters defined in the proposed mathematical model are summarized and explained in Table I and Table II respectively. All the parameters and variables are nonnegative. The variables defined to indicate the states of systems are binary variables, e.g. energy transmission state, ON/OFF state and charging/discharging state. The mathematical model presented in this section is a basic model for the building clusters operation decision models presented in Section 2.3.

Objective function

$$f_n = \sum_t (eGP_{n,t} \cdot PGp_t - eGs_{n,t} \cdot PGs_{n,t}) + \sum_t (fPGU_{n,t} \cdot PPGU_t + fBO_{n,t} \cdot PBO_t), \forall n \quad (2.1)$$

TABLE I: Decision variables in the proposed model

Variables for power grid	
$eGp_{n,t}$	Electricity purchased from power grid by building n at time t
$eGs_{n,t}$	Electricity sold back to power grid by building n at time t
Variables for local transaction market	
$eTin_{n,t}$	Electricity transmitted into building n from local transaction market at time t
$eTout_{n,t}$	Electricity contributed to local transaction market by building n at time t
$qCLTin_{n,t}$	Cooling energy transmitted into building n from local transaction market at time t
$qCLTout_{n,t}$	Cooling energy contributed to local transaction market by building n at time t
$qHLTin_{n,t}$	Heating energy transmitted into building n from local transaction market at time t
$qHLTout_{n,t}$	Heating energy contributed to local transaction market by building n at time t
$xEin_{n,t}$	Electricity transmission state of building n at time t
$xEout_{n,t}$	Electricity contribution state of building n at time t
$xCLin_{n,t}$	Cooling energy transmission state of building n at time t
$xCLout_{n,t}$	Cooling energy contribution state of building n at time t
$xHLin_{n,t}$	Heating energy transmission state of building n at time t
$xHLout_{n,t}$	Heating energy contribution state of building n at time t
Variables for combined cooling, heating and power (CCHP)	
$fPGU_{n,t}$	Fuel consumed by power generation unit in building n at time t
$fBO_{n,t}$	Fuel consumed by boiler in building n at time t
$qCC_{n,t}$	Thermal energy provided to cooling component in building n at time t
$qHC_{n,t}$	Thermal energy provided to heating component in building n at time t
$ePGU_{n,t}$	Electricity generated by power generation unit in building n at time t
$xPGU_{n,t}$	ON/OFF state of power generation unit in building n at time t
Variables for solar photovoltaic (PV)	
$ePV_{n,t}$	Electricity generated by PV in building n at time t
Variables for battery storage (BS)	
$eB_{n,t}$	Stored electricity in battery storage in building n at time t
$eBd_{n,t}$	Discharging rate of battery storage in building n at time t
$eBc_{n,t}$	Charging rate of battery storage in building n at time t
$xBc_{n,t}$	Charging state of battery storage in building n at time t
$xBd_{n,t}$	Discharging state of battery storage in building n at time t
Variables for thermal storage (TS)	
$qCTS_{n,t}$	Thermal energy provided to thermal storage by CCHP in building n at time t
$qTS_{n,t}$	Stored thermal energy in thermal storage in building n at time t
$qTSc_{n,t}$	Charging rate of thermal storage in building n at time t
$qTSd_{n,t}$	Discharging rate of thermal storage in building n at time t
$qTSH_{n,t}$	Thermal energy from thermal storage to heating component in building n at time t
$qTSC_{n,t}$	Thermal energy from thermal storage to cooling component in building n at time t
$qcTS_{n,t}$	Thermal energy from cooling process to thermal storage in building n at time t
$qhTS_{n,t}$	Thermal energy from heating process to thermal storage in building n at time t
$xTSd_{n,t}$	Discharging state of thermal storage in building n at time t
$xTSc_{n,t}$	Charging state of thermal storage in building n at time t

TABLE II: Parameters used in the proposed model

Parameters for power grid	
PGp_t	Electricity purchasing price in power grid at time t
PGs_t	Electricity selling price in power grid at time t
Parameters for building	
$PPGU_t$	Fuel price for power generation unit at time t
PBO_t	Fuel price for boiler at time t
$EL_{n,t}$	Electricity load in building n at time t
$QCL_{n,t}$	Cooling load in building n at time t
$QHL_{n,t}$	Heating load in building n at time t
Δt	Decision time interval, set to be 1 h
Parameters for combined cooling, heating and power (CCHP)	
$SPGU_n$	Size of power generation unit in building n
SBO_n	Size of boiler in building n
η_{PGU}	Efficiency of fuel-to-thermal conversion of power generation unit
η_{BO}	Thermal efficiency of boiler
η_C	Thermal efficiency of cooling component
η_H	Thermal efficiency of heating component
a_{PGU}	Coefficient of fuel-to-electricity conversion of power generation unit
b_{PGU}	Coefficient of fuel-to-electricity conversion of power generation unit
Parameters for solar photovoltaic (PV)	
Sol_t	Solar radiation at time t
SPV_n	Size of PV in building n
η_{PV}	Electricity generating efficiency of PV
Parameters for battery storage (BS)	
SBS_n	Size of battery storage in building n
EOB	Initial stored electricity in battery storage
η_{Bc}	Charging efficiency of battery storage
η_{Bd}	Discharging efficiency of battery storage
α_{Bmin}	Coefficient for minimum storage limit of battery storage
α_{Bcmax}	Coefficient for maximum charging limit of battery storage
α_{Bcmin}	Coefficient for minimum charging limit of battery storage
α_{Bdmax}	Coefficient for maximum discharging limit of battery storage
α_{Bdmin}	Coefficient for minimum discharging limit of battery storage
Parameters for thermal storage (TS)	
STS_n	Size of thermal storage in building n
$QOTS$	Initial stored thermal energy in thermal storage
η_{TSd}	Charging efficiency of thermal storage
η_{TSc}	Discharging efficiency of thermal storage
α_{TSmin}	Coefficient for minimum storage limit of thermal storage
α_{TScmax}	Coefficient for maximum charging limit of thermal storage
α_{TScmin}	Coefficient for minimum charging limit of thermal storage
α_{TSdmax}	Coefficient for maximum discharging limit of thermal storage
α_{TSdmin}	Coefficient for minimum discharging limit of thermal storage

The objective for each building is to minimize its energy cost including cost associated with power grid (the first term) and cost associated with CCHP system (the second term) in Equation 2.1

Constraints

Electricity load balance constraints

$$eGP_{n,t} + ePV_{n,t} + ePGU_{n,t} + eBd_{n,t} \cdot \eta_{Bd} + eTin_{n,t} = EL_{n,t} + eGs_{n,t} + \frac{eBc_{n,t}}{\eta_{Bc}} + eTout_{n,t}, \forall n, t \tag{2.2}$$

Electricity supply and demand should match at each time step for each building. On the left side, it's the energy coming from several supplies: purchased electricity from the power grid, generated electricity of PV panel and PGU unit in the CCHP, discharging energy of battery storage and transmitted electricity from the local transaction market. The electricity demand on right side consists of: electricity load, electricity sold back to the power grid, charging energy of battery storage and transmitted electricity into the local transaction market.

Thermal load balance constraints

$$(qCC_{n,t} + qTSC_{n,t}) \cdot \eta_C + qCLTin_{n,t} = QCL_{n,t} + qCLTout_{n,t} + qcTS_{n,t}, \forall n, t \tag{2.3}$$

$$(qHC_{n,t} + qTSH_{n,t}) \cdot \eta_C + qHLTin_{n,t} = QHL_{n,t} + qHLTout_{n,t} + qhTS_{n,t}, \forall n, t \tag{2.4}$$

Similarly, thermal energy (cooling and heating) are balanced by constraints in Equation 2.3 – Equation 2.4. Cooling/heating energy are supplied by boiler unit in the CCHP, discharging energy from thermal storage and transmitted thermal energy from the local transaction market to satisfy thermal demand, transmitted thermal energy into the local transaction market and charging energy of thermal storage.

Constraints for PV

$$ePV_{n,t} \leq SPV_n \cdot Sol_t \cdot \eta_{PV}, \forall n, t \tag{2.5}$$

Electricity generation of the PV panel can be estimated by its size, electricity generating efficiency of the PV panel and solar radiation.

Constraints for CCHP

a) Fuel consumption constraints

$$fBO_{n,t} \leq SBO_n, \forall n, t \tag{2.6}$$

$$fPGU_{n,t} \leq xPGU_{n,t} \cdot SPGU_n, \forall n, t \tag{2.7}$$

Fuel consumed by boiler and PGU units in the CCHP are limited by their maximum capacities.

b) Electricity generation constraint

$$ePGU_{n,t} \leq (fPGU_{n,t} - b_{PGU} \cdot xPGU_{n,t})/a_{PGU}, \forall n, t \tag{2.8}$$

Electricity generated by PGU is related to the fuel it consumed and its fuel-to-electricity conversion coefficient.

c) Thermal generation constraint

$$qCTS_{n,t} + qCC_{n,t} + qHC_{n,t} \leq \eta_{PGU} \cdot fPGU_{n,t} + \eta_{BO} \cdot fBO_{n,t}, \forall n, t \tag{2.9}$$

Thermal energy generated from PGU and boiler can be provided to cooling/heating components instantly or stored in thermal storage for later use.

Constraints for battery storage

a) Constraint for charging/discharging state

$$xBc_{n,t} + xBd_{n,t} \leq 1, \forall n, t \tag{2.10}$$

Battery storage cannot be charged and discharged at the same time.

b) Constraints for stored electricity

$$SBS_n \cdot \alpha_{Bmin} \leq eB_{n,t} \leq SBS_n, \forall n, t \tag{2.11}$$

$$eB_{n,1} = EOB + (eBc_{n,1} - eBd_{n,1}) \cdot \Delta t, \forall n \tag{2.12}$$

$$eB_{n,t} - eB_{n,t-1} = (eBc_{n,t} - eBd_{n,t}) \cdot \Delta t, \forall n, t \geq 2 \tag{2.13}$$

Electricity stored in battery storage should be kept between the permitted lowest level and its capacity (constraint in Equation 2.11), and is determined by charging/discharging activities (constraints in Equation 2.12 − Equation 2.13).

c) Constraints for electricity charging/discharging power

$$SBS_n \cdot \alpha_{Bcmin} \cdot xBc_{n,t} \leq eBc_{n,t} \leq SBS_n \cdot \alpha_{Bcmax} \cdot xBc_{n,t}, \forall n, t \tag{2.14}$$

$$SBS_n \cdot \alpha_{Bdmin} \cdot xBd_{n,t} \leq eBd_{n,t} \leq SBS_n \cdot \alpha_{Bdmax} \cdot xBd_{n,t}, \forall n, t \tag{2.15}$$

Charging/discharging power cannot excess the range of lowest and highest level.

Constraints for thermal storage

a) Constraint for charging/discharging state

$$xTSc_{n,t} + xTSd_{n,t} \leq 1, \forall n, t \tag{2.16}$$

Thermal storage cannot be charged and discharged at the same time.

b) Constraints for stored thermal energy

$$STS_n \cdot \alpha_{TSmin} \leq qTS_{n,t} \leq STS_n, \forall n, t \tag{2.17}$$

$$qTS_{n,1} = QOTS + (qTSc_{n,1} - qTSd_{n,1}) \cdot \Delta t, \forall n \tag{2.18}$$

$$qTS_{n,t} - qTS_{n,t-1} = (qTSc_{n,t} - qTSd_{n,t}) \cdot \Delta t, \forall n, t \geq 2 \tag{2.19}$$

Thermal energy stored in thermal storage should be kept between the permitted lowest level and its capacity (constraint in Equation 2.17), and is determined by charging/discharging activities (constraints in Equation 2.18 − Equation 2.19).

c) Constraints for thermal charging/discharging power

$$qCTS_{n,t} + qcTS_{n,t} + qhTS_{n,t} \leq STS_n, \forall n, t \tag{2.20}$$

$$qTSC_{n,t} + qTSH_{n,t} \leq qTSd_{n,t} \cdot \eta_{TSd}, \forall n, t \tag{2.21}$$

$$qTSc_{n,t} \leq (qCTS_{n,t} + qcTS_{n,t} + qhTS_{n,t}) \cdot \eta_{TSc}, \forall n, t \tag{2.22}$$

$$STS_n \cdot \alpha_{TScmin} \cdot xTSc_{n,t} \leq qTSc_{n,t} \leq STS_n \cdot \alpha_{TScmax} \cdot xTSc_{n,t}, \forall n, t \tag{2.23}$$

$$STS_n \cdot \alpha_{TSdmin} \cdot xTSd_{n,t} \leq qTSd_{n,t} \leq STS_n \cdot \alpha_{TSdmax} \cdot xTSd_{n,t}, \forall n, t \tag{2.24}$$

Constraint in Equation 2.20 defines that all the energy provided to thermal storage should be less than or equal to its capacity. Constraint in Equation 2.21 indicates the charging rate is constrained by the available energy to charge thermal storage. The amount of energy provided by thermal storage depends on its discharging rate (see constraint in Equation 2.22). Constraints in Equation 2.23 − Equation 2.24 are similar to constraints in Equation 2.14 − Equation 2.15.

Constraints for local transaction market

a) Constraints for electricity and thermal transaction state

$$xEin_{n,t} + xEout_{n,t} \leq 1, \forall n, t \tag{2.25}$$

$$xCLin_{n,t} + xCLout_{n,t} \leq 1, \forall n, t \tag{2.26}$$

$$xHLin_{n,t} + xHLout_{n,t} \leq 1, \forall n, t \tag{2.27}$$

At each time period, energy transmission states (in/out) are mutually exclusive in the interaction of each building with local transaction market.

b) Constraints for electricity and thermal transaction

$$eTin_{n,t} \leq M \cdot xEin_{n,t}, \forall n, t \tag{2.28}$$

$$eTout_{n,t} \leq M \cdot xEout_{n,t}, \forall n, t \tag{2.29}$$

$$qCLTin_{n,t} \leq M \cdot xCLin_{n,t}, \forall n, t \tag{2.30}$$

$$qCLTout_{n,t} \leq M \cdot xCLout_{n,t}, \forall n, t \tag{2.31}$$

$$qHLTin_{n,t} \leq M \cdot xHLin_{n,t}, \forall n, t \tag{2.32}$$

$$qHLTout_{n,t} \leq M \cdot xHLout_{n,t}, \forall n, t \tag{2.33}$$

Transmitted energy in the interaction of each building with local transaction market depends on the mutually exclusive transmission states, and M is a big number, normally used in mixed integer programming.

c) Balance constraints for local transaction market

$$\textstyle\sum_n eTin_{n,t} = \sum_n eTout_{n,t}, \forall t \tag{2.34}$$

$$\sum_n qCLTin_{n,t} = \sum_n qCLTout_{n,t}, \forall t \tag{2.35}$$

$$\sum_n qHLTin_{n,t} = \sum_n qHLTout_{n,t}, \forall t \tag{2.36}$$

Constraints in Equation 2.34 $-$ Equation 2.36 are used to balance energy supply and demand for local transaction market.

2.3 Balancing Collective and Individual Interests

In this section, we propose four different operation decision models to study the transactive energy management for the building clusters. The first model just focuses on maximizing the collective interests of the building clusters, and the second model is developed to maximize the collective interests and keep the individual interests at satisfactory levels. Both the collective and individual interests are maximized in the third and fourth models.

2.3.1 Operation Decision Models for Transactive Energy Management

To compare the performance of the building clusters operation with single building operation, we develop a reference model to find the total energy cost for all the buildings when they are disconnected and operated separately. The reference model is represented as:

$$[\textbf{Reference Model}]\begin{bmatrix} min f_0 = \sum_n f_{0,n} \\ s.t. Equation\ 2.2 - Equation\ 2.36 \\ xEin_{n,t} = 0, xEout_{n,t} = 0, \forall n, t \\ xCLin_{n,t} = 0, xCLout_{n,t} = 0, \forall n, t \\ xHLin_{n,t} = 0, xHLout_{n,t} = 0, \forall n, t \end{bmatrix} \tag{2.37}$$

where $f_{0,n}$ is the energy cost for the nth building in the reference model which is calculated using Equation 2.1.

Model I – maximizing collective interests

In the transactive energy network, each building can freely connect with other buildings to share information and exchange energy. In this model, we will focus on maximizing the collective interests of the building clusters which is to minimize the total energy cost. To this end, a mixed integer programming model is developed to study the operation decisions for the building clusters

$$[\textbf{Model I}]\left[\begin{array}{c} minf_I = \sum_n f_{I,n} \\ s.t. Equation\ 2.2 - Equation\ 2.36 \end{array}\right] \tag{2.38}$$

where $f_{I,n}$ is the energy cost for the nth building in the model I which is calculated using Equation 2.1.

Model II – maximizing collective interests subject to satisfactory individual interests

Although the model I can maximize the collective interests, it may not be able to guarantee the individual interest of each building which means some buildings have to spend more if they join the clusters. To guarantee each building can have cost savings in the clusters, we extend the model I by introducing a set of constraints.

$$f_{II,n} \leq f_{0,n} \cdot (1 - \theta), \forall n \tag{2.39}$$

where $f_{II,n}$ is the energy cost for the nth building in the model II which is calculated using Equation 2.1, $f_{0,n}$ represents the energy cost of the nth building in the reference model, θ is a parameter to indicate the percentage of cost savings expected by each building. The second model to maximize collective interests and keep a satisfactory level of individual interest is constructed as:

$$[\textbf{Model II}]\begin{bmatrix} min f_{II} = \sum_n f_{II,n} \\ s.t. Equation\ 2.2 - Equation\ 2.36, Equation\ 2.39 \end{bmatrix} \tag{2.40}$$

Model III – maximizing collective interests and relative individual interests

The second model considers both the collective and individual interests. However, the second model cannot answer the research question: can we maximize both the collective and individual interests. To address this question,we develop a third model based on min-max goal programming to investigate what is the maximum cost saving percentage each building can simultaneously achieve. In the proposed model, we introduce a variable η to represent the goal of each building which aims to achieve the percentage of cost savings as η comparing to the energy cost without joining the building clusters. One additional set of constraints are introduced to model the cost saving percentage for each building.

$$f_{III,n} \leq f_{0,n} \cdot (1 - \eta), \forall n \tag{2.41}$$

where $f_{III,n}$ is the energy cost for the nth building in the model III which is calculated using Equation 2.1. This model will maximize the cost saving percentage η to maximize the relative individual interest for each building in the clusters. The formulation of the proposed model is expressed as:

$$[\textbf{Model III}]\left[\begin{array}{c} max\,\eta \\ s.t. Equation\ 2.2 - Equation\ 2.36, Equation\ 2.41 \end{array}\right] \tag{2.42}$$

Model IV − maximizing collective interests and absolute individual interests

In the fourth model, we introduce three parameters to model the local transaction market which are LPE_t, LPC_t, LPH_t representing the price for electricity, cooling and heating energy of the local transaction market respectively. This model aims to evenly distribute the cost saving of the building clusters to each building to maximize the absolute individual interests. A variable ϕ and a set of constraints are introduced to model this cost saving.

$$f_{IV,n} + \phi \leq f_{0,n}, \forall n \tag{2.43}$$

The local energy market is considered in the fourth model, and the energy cost for the nth building $f_{IV,n}$ is calculated as

$$f_{IV,n} = \left\{\begin{array}{c} \sum_t (eGp_{n,t} \cdot PGp_t - eGs_{n,t} \cdot PGs_{n,t}) + + \sum_t (fPGU_{n,t} \cdot PPGU_t + fBO_{n,t} \cdot PBO_t) \\ + \sum_t LPE_t \cdot (eTin_{n,t} - eTout_{n,t}) + \sum_t LPC_t \cdot (qCLTin_{n,t} - qCLTout_{n,t}) \\ + \sum_t LPH_t \cdot (qHLTin_{n,t} - qHLTout_{n,t}) \end{array}\right\} \tag{2.44}$$

Therefore, the formulation of the fourth model is expressed as

$$[\textbf{Model IV}] \begin{bmatrix} max\, \phi \\ s.t. Equation\ 2.2 - Equation\ 2.36, \\ Equation\ 2.43, Equation\ 2.44 \end{bmatrix} \tag{2.45}$$

2.3.2 Experimental Results Analysis for Operation Decision Models

In this research, we study a cluster of sixteen commercial building level buildings located in Chicago, U.S. One-month data for electricity and thermal load profiles for these sixteen buildings are collected. The basic information of these buildings and their reference load profiles in the climate zone of Chicago can be found in Refs. (24)(96). Solar radiation for the Chicago area in year 2010 is used (86). Commercial and industrial time-of-use rate from Ref. (75) is adopted for electricity purchasing price from the power gird. Sizes of all the energy systems are defined based on the buildings' maximum load. All the other parameters have the same settings as parameters in Ref. (23). All experiments implemented in this section are solved by a MIP engine of CPLEX with a relative gap of 0.005.

Model I analysis

To study the cost savings of clustering buildings, we get the energy cost for each single building without clustering as reference. After running the reference model, the energy cost of each building is recorded in Table III. The total energy cost for these sixteen separate buildings is $87,793.56. The negative value indicates that the building can gain revenue by selling surplus energy to the power grid. Next, all the buildings are taken account into the first operation decision model (see Equation 2.38) to explore the potential cost benefit of clustering. The result in Table III shows that there is 15.34% cost savings for these sixteen buildings if they form clusters to exchange energy.

TABLE III: Analysis of the building clusters using the model I.

building index	Cost in reference model ($f_{0,n}$)($)	Cost in model I ($f_{I,n}$)($)	Amount of cost saving ($)	Percentage of cost saving (%)
1	79.43	-38.77	118.20	148.81%
2	1465.71	291.77	1173.94	80.09%
3	21299.05	41033.72	-19734.67	-92.66%
4	-440.18	-6.88	-433.30	-98.44%
5	399.93	-52.45	452.38	113.12%
6	376.03	-12.77	388.80	103.40%
7	453.17	971.61	-518.44	-114.40%
8	11361.60	5170.06	6191.55	54.50%
9	3987.67	2532.37	1455.30	36.49%
10	680.01	144.75	535.25	78.71%
11	969.50	393.91	575.59	59.37%
12	32440.07	16852.13	15587.95	48.05%
13	4786.38	2477.27	2309.11	48.24%
14	1773.94	285.04	1488.90	83.93%
15	7395.27	4211.05	3184.22	43.06%
16	765.99	69.53	696.46	90.92%
Total cost	87793.56	74322.33	13471.23	15.34%

It is observed from Table III that some buildings cost more if they join the clusters, such as building 3, 4, and 7. If all the buildings are operated by one operator, then it will be fine for all the buildings to form clusters. Otherwise, high cost sacrificing for buildings 3, 4, and 7 will prohibit their motivation to join the clusters. It is concluded that the first model can maximize the collective interests, but the individual interests are ignored.

Model II analysis

As shown in previous analysis, approximately 15.34% cost savings can be expected if the electricity and thermal energy can be freely shared and exchanged among the buildings in the clusters. To guarantee each building can have cost savings in the clusters, we will use the second model developed in Section 2.3.1 to study the building clusters. We change the values of q from 0, 0.05, 0.10, to 0.14 and run the second operation decision model. The percentages of energy cost savings for each building in the clusters with different θ values are demonstrated in Figure 6.

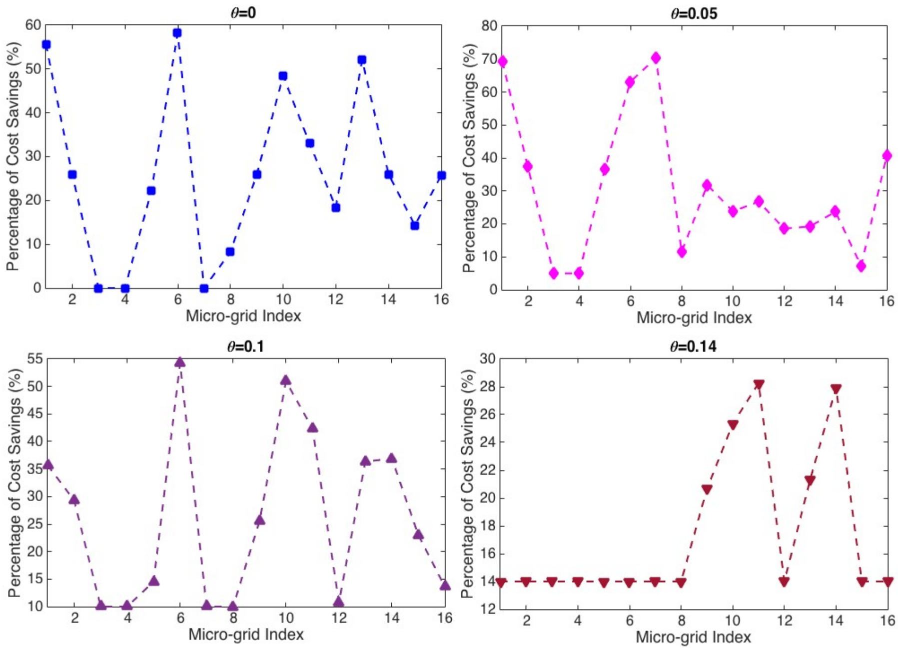


Figure 6: Percentages of energy cost savings for each building using the model II

TABLE IV: Total energy cost comparison for the model I and II.

Decision model	Total cost ($)
Reference model	87793.56
Model I	74322.33
Model II with θ=0	74272.72
Model II with θ=0.05	74205.79
Model II with θ=0.10	74241.39
Model II with θ=0.14	74300.87

As shown in Figure 6, varied percentages of cost savings occur for different buildings in the clusters even with the same θ values. For example, building 1 has almost 70% cost savings at θ=0.05 while the buildings 3 and 4 just have 5% cost savings. More buildings start to converge to a same percentage of cost savings when the values of θ are increased. On the other hand, as demonstrated in Table IV, the total energy costs of the building clusters with different θ values stay the same as the building clusters in the model I. Please note due to the rounding errors, we may see different values of total energy cost for different models. We consider the values of the total energy cost are the same if their differences are within 0.5% (the relative gap we defined in CPLEX). It is concluded that the model II can maximize the collective interests and keep the individual interests of each building at satisfactory levels. The set of constraints in Equation 2.39 can redistribute the cost savings of the clusters to each building to satisfy its individual interests. We have another observation that the second model is infeasible when θ is greater than 15.34% which indicates each building cannot simultaneously achieve the cost saving percentage higher than the building clusters.

Model III analysis

The third model is developed to study what is the maximum percentage of energy cost savings each building can achieve simultaneously, and whether all the buildings can achieve the same percentage of energy cost savings as the clusters. After running the model III, the energy cost for each building are recorded in Table V. It is demonstrated that all the buildings have the same percentage of energy cost saving percentage 15.34%. Please note due to the rounding errors, we have different percentages of energy cost savings for the building clusters presented in Table III (e.g., 15.34%) and Table V (e.g., 15.49%). We consider the values of the total energy cost are the same if their differences are within 0.5% (the relative gap we defined in CPLEX), therefore we can consider 15.34% and 15.49% as the same. It is concluded that all the buildings can have the same percentage of energy cost savings as the building clusters, and the model III can maximize both the collective and individual interests.

Model IV analysis

The third model developed in 2.3.1 defines the individual interest as the relative percentage of energy cost savings to redistribute the cost savings to each building. However, it cannot evenly distribute the absolute amount of cost savings to each building. One straightforward thought to ensure absolute individual interests for each building is to divide the total cost savings of building clusters evenly to each building, which is (\$87793.56 - \$74322.33)/16 = \$841.95. This value depends on the total energy cost of the building clusters which is not likely to be known in advance.

In the fourth model, the prices of electricity and thermal energy are introduced into the local transaction market to drive energy transaction behavior of each building. The best local

TABLE V: Analysis of the building clusters using the model III.

building index	Cost in reference model ($f_{0,n}$)($)	Cost in model III ($f_{III,n}$)($)	Amount of cost saving ($)	Percentage of cost saving (%)
1	79.43	67.25	12.18	15.34%
2	1465.71	1240.91	224.80	15.34%
3	21299.05	18032.41	3266.64	15.34%
4	-440.18	-507.69	67.51	15.34%
5	399.93	338.59	61.34	15.34%
6	376.03	318.36	57.67	15.34%
7	453.17	383.67	69.50	15.34%
8	11361.60	9619.07	1742.53	15.34%
9	3987.67	3376.08	611.59	15.34%
10	680.01	575.71	104.29	15.34%
11	969.50	820.80	148.69	15.34%
12	32440.07	27464.73	4975.34	15.34%
13	4786.38	4052.29	734.09	15.34%
14	1773.94	1501.87	272.07	15.34%
15	7395.27	6261.05	1134.21	15.34%
16	765.99	648.51	117.48	15.34%
Total cost	87793.56	74193.62	13599.94	15.49%

energy transaction price will be the price that makes each local building saves around $841.95. In this research, the price range ($PGs_t \sim PGp_t$, $0 \sim \$0.04$, $0 \sim \$0.04$) is considered for LPE_t, LPC_t, LPH_t, where PGs_t and PGp_t are price of energy that sold back and purchased from the main power grid. The value of $0.04 is the maximum price of cooling and heating that the local energy market will consider, which is estimated by the fuel cost for generating one unit cooling or heating energy. In this experiment, five different price levels from low to high are examined, which are Level A: (PGs_t, 0, 0), Level B: ($PGs_t + (PGp_t\text{-}PGs_t)/4$, 0.01, 0.01), Level C: ($PGs_t + (PGp_t\text{-}PGs_t)/2$, 0.02, 0.02), Level D: ($PGs_t + 3\cdot(PGp_t\text{-}PGs_t)/4$, 0.03, 0.03), and Level E: (PGp_t, 0.04, 0.04). The energy cost for each building and the total energy costs for the building clusters under different price levels are shown in Table VI. The absolute amount of energy cost savings (ϕ) is increased and the total energy cost is decreased when the local energy transaction price is changed from low to high. As it can be observed from Table VI, there exists an optimal local transaction price that can ensure maximum absolute amount of energy cost savings for each building in the clusters. The optimal price is in range between (PGs_t + 3$\cdot$(PGp_t-PGs_t)/4, 0.03, 0.03) and (PGp_t, 0.04, 0.04). It is concluded that the model IV can maximize both the collective and individual interests where the individual interests are defined as the absolute amount of energy cost savings for each building.

TABLE VI: Energy cost savings for the building clusters under different pricing levels using the model IV.

building index	Cost in reference model ($f_{0,n}$)($)	Cost under level A ($)	Cost under level B ($)	Cost under level C ($)	Cost under level D ($)	Cost under level E ($)
1	79.43	-68.16	-494.49	-591.39	-761.49	-763.40
2	1465.71	1318.12	891.79	794.89	624.79	622.88
3	21299.05	21151.46	20725.13	20628.23	20458.13	20456.22
4	-440.18	-587.77	-1014.10	-1111.00	-1281.10	-1283.01
5	399.93	252.34	-173.99	-270.89	-440.99	-442.90
6	376.03	228.45	-197.89	-294.79	-464.89	-466.80
7	453.17	305.58	-120.75	-217.65	-387.75	-389.66
8	11361.60	11214.02	10787.69	10690.78	10520.68	10518.77
9	3987.67	3840.08	3413.75	3316.85	3146.75	3144.83
10	680.01	532.42	106.09	9.19	-160.91	-162.82
11	969.50	821.91	395.58	298.67	128.58	126.66
12	32440.07	32292.49	31866.16	31769.25	31599.15	31597.24
13	4786.38	4638.79	4212.46	4115.56	3945.46	3943.55
14	1773.94	1626.36	1200.02	1103.12	933.02	931.11
15	7395.27	7247.68	6821.35	6724.45	6554.35	6552.44
16	765.99	618.41	192.08	95.17	-74.93	-76.84
ϕ	–	147.59	573.92	670.82	840.92	842.83
Total cost	87793.56	85432.20	78610.87	77060.43	74338.84	74308.26

Results summary and discussion

The minimum, maximum, and average amounts of energy cost saving and percentages of energy cost savings for the sixteen buildings and the total energy cost for the building clusters using the four operation decision models are summarized in Table VII. It is demonstrated that the model I, II, III and IV with appropriate local energy pricing settings can maximize the collective interests of the building clusters. The model III can maximize the individual interests in terms of the relative percentages of cost savings for each building, and the model IV can maximize the individual interests in terms of the absolute amount of cost savings for each building. The model III has a large variance of the amount of energy cost savings for each building, and the model IV has a large variance of the percentage of energy cost savings for each building.

TABLE VII: Results summary for models I $\sim$ IV

Model	Amount of cost savings ($)			Percentage of cost savings ($)			Total Cost ($)
	Min	Max	Average	Min	Max	Average	
Model I	-19734.67	15587.95	841.95	-114.40%	148.81%	42.70%	74322.33
Model II, θ=0	0.00	5963.53	845.05	0.00%	58.18%	25.87%	74272.72
Model II, θ=0.05	22.01	6018.76	849.24	5.00%	70.30%	30.62%	74205.79
Model II, θ=0.1	28.34	3502.57	847.01	10.00%	54.26%	25.83%	74241.39
Model II, θ=0.14	11.12	4541.61	843.29	14.00%	28.26%	17.34%	74300.87
Model III	12.18	4975.34	850.00	15.34%	15.34%	15.34%	74193.62
Model IV, level A	147.59	147.59	147.59	0.45%	185.81%	25.87%	85432.20
Model IV, level B	573.92	573.92	573.92	1.77%	722.56%	100.59%	78610.87
Model IV, level C	670.82	670.82	670.82	2.07%	844.56%	117.57%	77060.43
Model IV, level D	840.92	840.92	840.92	2.59%	1058.71%	147.38%	74338.84
Model IV, level E	842.83	842.83	842.83	2.60%	1061.12%	147.72%	74308.26

The first model can be applied in the scenarios that all the buildings are operated by one manager. When the buildings are managed or operated by different managers, the second, third and fourth models are more appropriate. The second model is preferred in the scenarios that the buildings have heterogeneous individual interests (e.g., different satisfactory levels for the percentages of energy cost savings), and the third and fourth models are for homogeneous individual interests. The third model is better for the buildings to reach an equilibrium solution to maximize each building's percentage of energy cost savings. This is more appropriate to be used in the scenarios that the contributions of each building to the clusters are ranked. The fourth model is preferred in the scenarios that each building wants to obtain an equal amount of energy cost savings. This model may not be fair to the buildings which have large contributions to maximize the collective interests of the building clusters, and is more appropriate to the highly cooperative building clusters.

2.4 Concluding Remarks

In the context of the smart grid, the building can cluster with other buildings in its neighborhood to form transactive network to exchange and trade energy. It is demonstrated that the building clusters can achieve some collective benefits, such as minimizing total energy cost, total primary energy consumption, and total carbon dioxide emissions. Using the existing building clusters operation decision models, some buildings may cost more if they join the clusters which will significantly impact these buildings motivation to form clusters. In this research, we propose four different models to study the transactive energy management for building clusters. The first model just focuses on maximizing collective interests, and the second model aims to maximize collective interests within a satisfactory level of individual interests. Both the collective and individual interests are maximized in the third and fourth models. The local energy transaction market is modeled in the fourth model. It is concluded from the experimental results that: 1) the building clusters can achieve 15.34% of energy cost savings comparing to building without clustering, 2) each building can simultaneously achieve the same percentage of energy cost savings as the building clusters, 3) each building can simultaneously achieve the same amount of energy cost savings as the building clusters, and 4) the energy pricing in the local energy market can be optimally determined using our proposed models.

CHAPTER 3

DISTRIBUTED DECISION APPROACH FOR DISTRIBUTION SYSTEM OPERATOR

Recently, existing research has demonstrated that more benefits of energy cost saving, environmental sustainability and reliable power supply can be achieved by clustering buildings together to freely exchange information and energy. To enable efficient transactive operation among buildings in the cluster, both centralized and distributed decision approaches were developed in the recent decades. However, most of the existing approaches are only applicable for small scale building clusters and/or the privacy of each stakeholder (e.g., building) is not well protected. To bridge these research gaps, we propose a swarm intelligence based bi-level distributed decision approach. A particle swarm optimizer is employed at the system level to coordinate the transactive operations among buildings, and a mixed integer programming model is developed for each building to simultaneously obtain operation decisions for its energy systems. The only information exchanged between the system level and building level is the marginal price of transactive energy which can protect the private information for each building. The performance of the proposed decision approach in terms of accuracy, scalability, and robustness is evaluated using various building clusters with the number of buildings from 2 to 256. It is demonstrated that our proposed approach is very computationally efficient, scalable and robust, and the computational complexity is $O(n)$ where n is the number of buildings in the cluster.

3.1 Transactive Operations for Cooperative Buildings

As reviewed in Section 1.2 that, building clusters or building level micro-grid clusters are more energy efficient than a single building or micro-grid, and cooperation between multiple buildings or micro-grids has been gained more and more attention very recently. As a promising method to improve economic efficiency, buildings or micro-grids with complementary energy profiles have motivation to cooperate with each other and perform direct energy trading due to lower costs and power losses. A multi-party energy management model for smart building cluster is proposed based on non-cooperative game theory (74). Coalitional game has been formulated to study cooperative strategies between the micro-grids of a distribution network. A three-stage algorithm based on coalitional game strategy is proposed which includes request exchange stage, merge-and-split stage and cooperative transaction stage to enable micro-grids to form coalitions and exchange power directly (90). In order to form cooperative micro-grids, a hierarchical priority based coalition scheme is proposed to provide the optimal coalition, where the optimality of the formed coalitions is proved by coalitional game theory (13) and greedy based strategy is designed to perform network constrained energy exchange within a formed coalition. Pricing mechanism for interconnected smart micro-grids is developed based on game theory and the present mathematical model captures the energy losses, real-time cost and production to optimize the overall losses and total production costs (9). Another price mechanism is developed for the energy exchange among buildings which can guarantee the fairness of all the buildings by introducing Lagrangian multipliers as the coordinated signals (139). A distributed algorithm that supports autonomous operation for a set of isolated micro-grids is proposed using a complete information game theoretic approach via coalition formation formulation (45). The proposed algorithm empowers the micro-grids to coordinate and match significant part of energy demand and supply with cooperating micro-grids. Coalitional game is formulated for a number of micro-grids that serve a group of consumers, and a cooperation algorithm is proposed to allow the micro-grids autonomously cooperate and self-organize into a partition composed of disjoint micro-grid coalitions (111). Self-adaptability to environmental changes such as variations in the demand is also considered in the algorithm.

Excluding the coalitional game among multiple buildings or building level micro-grids, different coordination approaches have been developed for distributed decision framework where buildings or micro-grids are treated as distributed intelligent agents. A self-organizing computing framework, based on self-organizing agents, is conceptualized and equipped with decentralized consensus protocols for solving the fundamental control and monitoring problems of smart micro-grids without the need for centralized data acquisition and processing (129). An agent-based demand side management framework provides an intelligent solution to shorten supply-demand gap in micro-grids by forming virtual market that allows neighboring micro-grids to trade energy with each other (68). To encourage resource sharing among different autonomous micro-grids and solve energy imbalance problems self-adaptively, layered cooperative control framework is presented where corresponding negotiation algorithms are introduced based on multi-agent system to model coordination behaviors of interconnected micro-grids (73). The optimal control problem of coupled micro-grids is modeled as a decentralized partially-observable Markov decision process, and a coordinated dynamic programming algorithm is used to solve the problem sequentially by introducing a look-ahead dual multiplier mechanism as decentralized control signals from centralized information (135). Hierarchical power scheduling approach is investigated to optimally manage power trading, storage, and distribution in a smart power grid with a macro-grid and cooperative micro-grids (133). The problem is decomposed into a two-tier formulation solved by online and distributed algorithms.

In addition to the abovementioned distributed decision approaches that are popularly adopted for cooperative buildings, some other distributed frameworks are also widely studied and applied in different areas, for example analytical target cascading (ATC) and collaborative optimization (CO). ATC and CO are utilized heavily for complex engineering design that can be approached by decomposition (6; 118). In the chassis design of a sport-utility vehicle, ride quality and handling targets are cascaded down to systems and subsystems utilizing suspension, tire, and spring analysis models (64). For a typical nested solution strategy of ATC, coupled sub-problems are solved in the inner loop and penalty multipliers are updated in the outer loop where different penalty methods can be used, such as quadratic penalty function (82), exponential penalty function (26), Lagrangian penalty function (119), etc. Based on ATC method, security-constrained unit commitment problem is decomposed into several scalable zones which are interconnected through tie lines (59; 60). By introducing a virtual zone and auxiliary variables, master problem is formulated in order to coordinate and parallelize the solving of subsystems iteratively using augmented Lagrangian function. A collaborative decision process for an interdisciplinary low energy building design is studied where two disciplines at subsystem level focus on initial envelope investment and total energy consumption respectively (18).

After dividing the structural optimal design into three concurrent subspaces (structural layout optimization, shape optimization and size optimization), concurrent collaborative optimization technique is developed to solve the sub-problems independently at each iteration loop (140). A goal-programming enhanced multi-objective collaborative optimization approach is put forward to facilitate the optimization process over trade-off design spaces of engineering systems (118).

Although various distributed decision frameworks have been developed and applied for energy system operation, most of the existing distributed implementations are not absolutely parallelized or have relatively complex structures such as peer-to-peer structure. It prohibits their applications for large scale building clusters. In addition, the existing distributed decision frameworks require extensive information (e.g., detailed decision models) to be exchanged among different decision agents which is not able to protect the private information of decision agents. To bridge these research gaps, we propose a swarm intelligence based bi-level distributed decision framework to model the energy transactions in the building clusters. At the system level, a particle swarm optimizer (PSO) is employed to coordinate all the buildings to dispatch shared energy and enable energy transactions in the clusters. Given the amount of transacted energy determined from the system level, each building at the sub-system level will employ a mixed integer programming model to obtain operation decisions for its energy systems, such as distributed generators and energy storage systems. To enable efficient coordination among different buildings and protect the private information of each building, a marginal price based feedback strategy is proposed. After each building solves its local decision model, the marginal prices for exchanged energy will be calculated and fed back to the system level. An updated energy transaction decision will be obtained based on the marginal prices received from all the buildings. To demonstrate the accuracy, robustness and scalability of the proposed decision framework, various building clusters with number of buildings from 2 to 256 are evaluated.

In summary, the contributions of this Chapter can be summarized as: 1) a distributed decision model is developed to study the energy transactions among spatially distributed buildings in the clusters, 2) a computationally efficient, scalable, and robust distributed decision framework based on swarm intelligence is developed, and 3) the proposed distributed decision framework provides enabling technology for large scale building clusters operation which can be extended for smart city applications.

3.2 Distributed Transactive Framework for Cooperative Buildings

Based on study in Chapter 2, a distributed modeling framework is developed for building clusters (see Figure 7) to study energy transactions in local transaction market with multiple buildings participated. Each building has three modules: 1) load module which considers electricity, cooling and heating load, 2) generating module which considers solar photovoltaic (PV) panel and CCHP system, and 3) storage module which considers electric and thermal energy storage. The details about electricity and thermal energy flow among these three modules within each building can be found in Chapter 2. From an overall perspective, three kinds of load (electricity, cooling and heating) within each building should be satisfied and each building can share and exchange energy with other buildings through a local transaction market.

As shown in Figure 7, the proposed distributed energy transaction framework has two levels, system level and subsystem level. Power grid is assumed to support electricity purchasing and

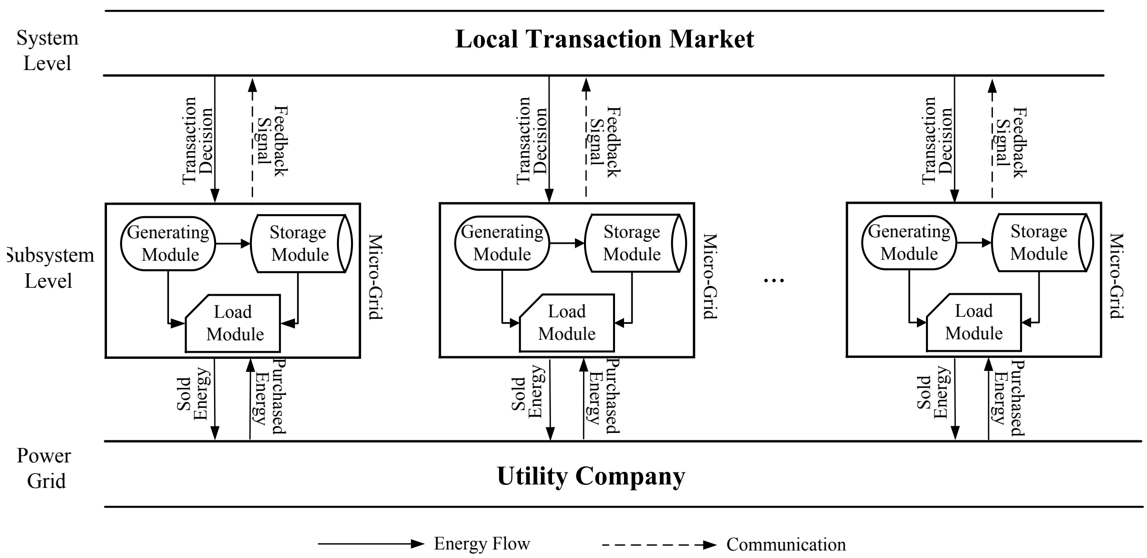


Figure 7: Bi-level distributed energy transaction framework for building clusters

selling for buildings. At subsystem level, with the objective of minimizing its energy cost f_m, the operation model (Chapter 2) for each building m at each time period t is formulated using six groups of constraints. The electricity load balance constraints is shown in Equation 2.2.

$$
\begin{aligned}
& eGp_{m,t} + ePV_{m,t} + ePGU_{m,t} + eBd_{m,t} \times \eta + eTin_{m,t} \\
& = EL_{m,t} + eGs_{m,t} + \frac{eBc_{m,t}}{\eta} + eTout_{m,t}
\end{aligned}
$$

On the left side of Equation 2.2, it's the energy coming from several supplies: purchased electricity from power grid (eGp), generated electricity from solar panel (ePV) and generation unit in CCHP ($ePGU$), discharged electricity of battery storage ($eBd \times \eta$, discharging and charging process are set to have same efficiency η) and transmitted electricity from local transaction market ($eTin$). The electricity demand on right side consists of: electricity load (EL), electricity sold back to power grid (eGs), charged electricity of battery storage (eBc/η) and transmitted electricity into local transaction market ($eTout$). The connection between system level and each building at subsystem level is the transmitted electricity ($eTin$ and $eTout$). At system level, total $eTin$ and total $eTout$ should be balanced ($\sum_{m=1}^{M} eTin_{m,t} = \sum_{m=1}^{M} eTout_{m,t}$ where M is the total number of buildings in the cluster). We assume $eTin$ and $eTout$ cannot simultaneously exist for the building at each time period.

In an iterative solution approach, both $eTin$ and $eTout$ will be assigned to each building after some balancing processes at the system level. Then at the subsystem level, each building will make its own operation decisions depending on the assigned energy transaction. Different from most of existing approaches, the distributed energy transaction framework proposed here has three main advantages: 1) autonomous operation can be realized for participated buildings at the subsystem level in a real parallel way, 2) comparing with peer-to-peer structure, the bi-level structure can be easily expanded with more buildings joining or disjoining the cluster, 3) private information (e.g. load profile, energy system configuration, etc.) of each building can be protected during the cooperation process. The coordination algorithm used at the system level will be discussed in details in the following section.

3.3 Distributed Coordination Algorithm for DSO

Particle swarm optimization (PSO), a widely used swarm intelligence approach, was firstly developed in 1995 (28; 61) which mimics a flock of birds that communicate together as they fly. Since then, PSO has gained popularity increasingly implied by large amount of emerging literature. This is supported by extensive experimental studies (30; 46; 62; 31) which have demonstrated that PSO may outperform other population-based evolutionary algorithms including genetic algorithms, memetic algorithms, differential evolution, ant-colony optimization and shuffled frog leaping in terms of solution quality and computational efficiency on some optimization problems (51; 52). A large number of PSO variants have been proposed for different specific problems from improving basic PSO formulation, neighborhood topologies or learning strategies for each particle (51). Due to its simplicity and outstanding performance, PSO is adopted here for distributed transactive operation of building clusters.

3.3.1 Basic PSO and Marginal Price Overview

In canonical PSO with inertia weight, the velocity and position for particle p at iteration i are updated as (115),

$$\mathbf{v}_p^{i+1} = w \times \mathbf{v}_p^i + c_1 \times r_{1,p}^i \times \left(\mathbf{p}_p^i - \mathbf{x}_p^i\right) + +c_2 \times r_{2,p}^i \times \left(\mathbf{p}_g^i - \mathbf{x}_p^i\right) \tag{3.1}$$

$$\mathbf{x}_p^{i+1} = \mathbf{x}_p^i + \mathbf{v}_p^{i+1} \tag{3.2}$$

where D-dimensional vector $\mathbf{v}_p^i$ and $\mathbf{x}_p^i$ are the velocity and position of the pth particle at iteration i; $\mathbf{p}_p^i$ is the best position found so far by the pth particle and $\mathbf{p}_g^i$ is the best position found so far by the swarm; w is the inertia weight which determines how much influence previous velocity has on velocity for the next iteration; $r_{1,p}^i$ and $r_{2,p}^i$ are two independent random numbers uniformly distributed on [0, 1]; c_1 and c_2 are two learning factors, representing the attractions that a particle has toward its own success $\mathbf{p}_p^i$ and the swarm's best position $\mathbf{p}_g^i$, called cognitive learning factor and social learning factor respectively.

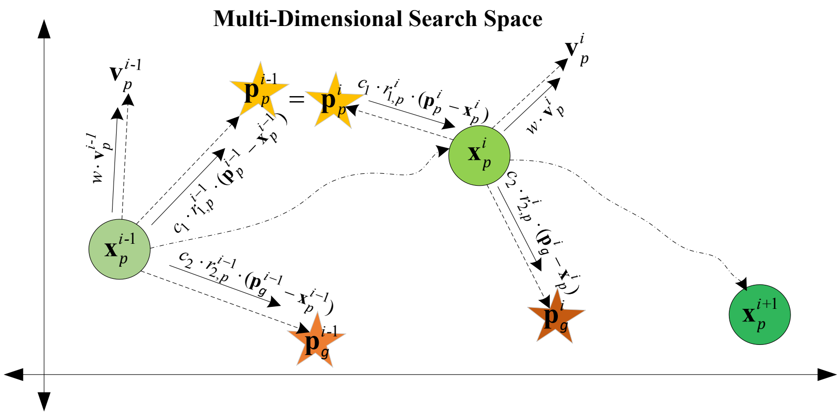


Figure 8: Iteration process of a particle in PSO

As shown in Equation 3.1, the velocity of each particle p for the next iteration $\mathbf{v}_p^{i+1}$ is composed of three main parts: a memory of current flight direction (first term), self-cognition coming from its own experience (second term) and social communication with neighbors in the swarm (third term). In Equation 3.2, current position of each particle $\mathbf{x}_p^i$ represents a coordinate describing a point in the searching space and is evaluated as a problem solution. If this solution $\mathbf{x}_p^i$ is better than the best solution found so far by particle p, then it will be stored as $\mathbf{p}_p^i$, and if this solution $\mathbf{x}_p^i$ is better than the best solution found so far by all particles, it will be stored as $\mathbf{p}_g^i$. The next coordinate of particle p, $\mathbf{x}_p^{i+1}$ will be chosen by adding a step size $\mathbf{v}_p^{i+1}$ to its current coordinate $\mathbf{x}_p^i$. The iteration process of the particle can be illustrated in Figure 8.

In economics, marginal price (or marginal cost) equals to the extra cost of producing extra unit of product (97). This price includes any additional costs required to produce the next unit, and it usually varies depending on current production level and time period being considered. However, in optimization area, for virtual optimization model where the production maybe infinitely divisible or continuous, increment of one unit won't be applied anymore. To make the definition of marginal price consistent in general case, the differential meaning ($d(Cost)/d(Quantity)$) is usually adopted in literature (11; 105) instead of unit change, if the cost function is not differentiable, the marginal price could be expressed as $\Delta(Cost)/\Delta(Quantity)$.

Marginal analysis plays a crucial role to support decision making in managerial economics. The basic purpose of marginal analysis is to balance the costs and benefits of additional actions, and the optimal activity level will be at the point where marginal cost equals to marginal benefit. For example, in Figure 9, for a certain resource, the profit improving space can be defined by the difference of marginal cost and marginal revenue, and the optimal production level to maximize profit will be at Level 2 (L2) which can be sold at market price 2 (P2). It clearly shows about how much of an activity should be undertaken to decision makers than average costs, fixed costs and sunk costs or any other irrelevant costs.

Besides being primarily used in business management to either maximize profits or minimize losses, marginal analysis also has been applied to other areas. For example, the concept is

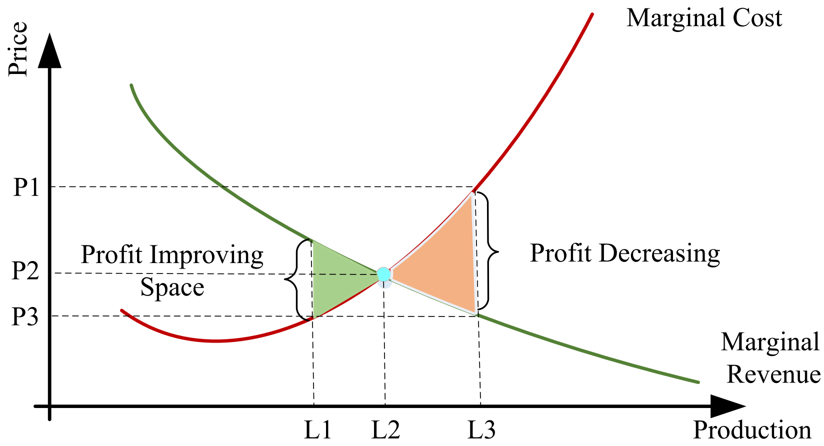


Figure 9: Profit space indicated by marginal price

applied to determine what number of contractors should be considered given fixed budget to minimize cost without being inefficient (130). In health services, marginal effect could quantify changes in terms of probability of readmission, number of prescriptions, number of hospital admission days, number of physician office visits and days of survival (waiting time) due to changes in independent variables of interest (95; 94). Marginal emission savings vs. additional economic margins is analyzed to support policy making towards climate change mitigation goals (78). Marginal value is also utilized in a dynamic, price-directed heuristic to find an optimal cyclic schedule for classic sequence-dependent economic lot scheduling problem (1).

Despite of the wide range of applications, marginal price is only used to assist decision making for a single agent in a single time stage mostly, and the potentials of utilizing marginal price to coordinate production level among multiple agents given scarce resources for better collective interest haven't been explored yet in current literature.

3.3.2 Marginal Price Based PSO for Distributed Decision

Considering cost saving potential reflected by marginal price, a marginal price based particle swarm algorithm (MP-PSO) is proposed in this section for energy transaction. Two additional modules are designed in the MP-PSO based decision framework: (1) Feasibility Module, and (2) Feedback Module (filled blocks in Figure 10).

In MP-PSO, the real number encoded position particle is used to represent transactive energy for the buildings at each time period and the fitness of the particle is the total system cost of the building clusters. Since the transmitted energy $eTin_{m,t}$ and $eTout_{m,t}$ cannot exist simultaneously for each building, $eTin_{m,t}$ and $eTout_{m,t}$ can be represent by only one value in a D-dimensional position particle vector ($\mathbf{eT}$) (suppose dimension d is corresponding to the assigned energy transaction for building m at time period t, if the value at this dimension $\mathbf{eT}(d)$ is positive, then $eTin_{m,t} = \mathbf{eT}(d)$ and $eTout_{m,t} = 0$; if $\mathbf{eT}(d)$ is negative, $eTin_{m,t} = 0$ and $eTout_{m,t} = \mathbf{eT}(d)$). Learning factors c_1, c_2 and inertia weight w in MP-PSO are adjusted at each iteration according to nonlinear acceleration strategy (103) and random generation strategy (103; 29) separately. It is set to 1) mutate half of the particles' positions and reset each dimension of the chosen particles randomly when the improvement of total system cost is lower than predefined tolerance in successive two iterations, and 2) stop the algorithm if the improvement is lower than tolerance for successive four iterations.

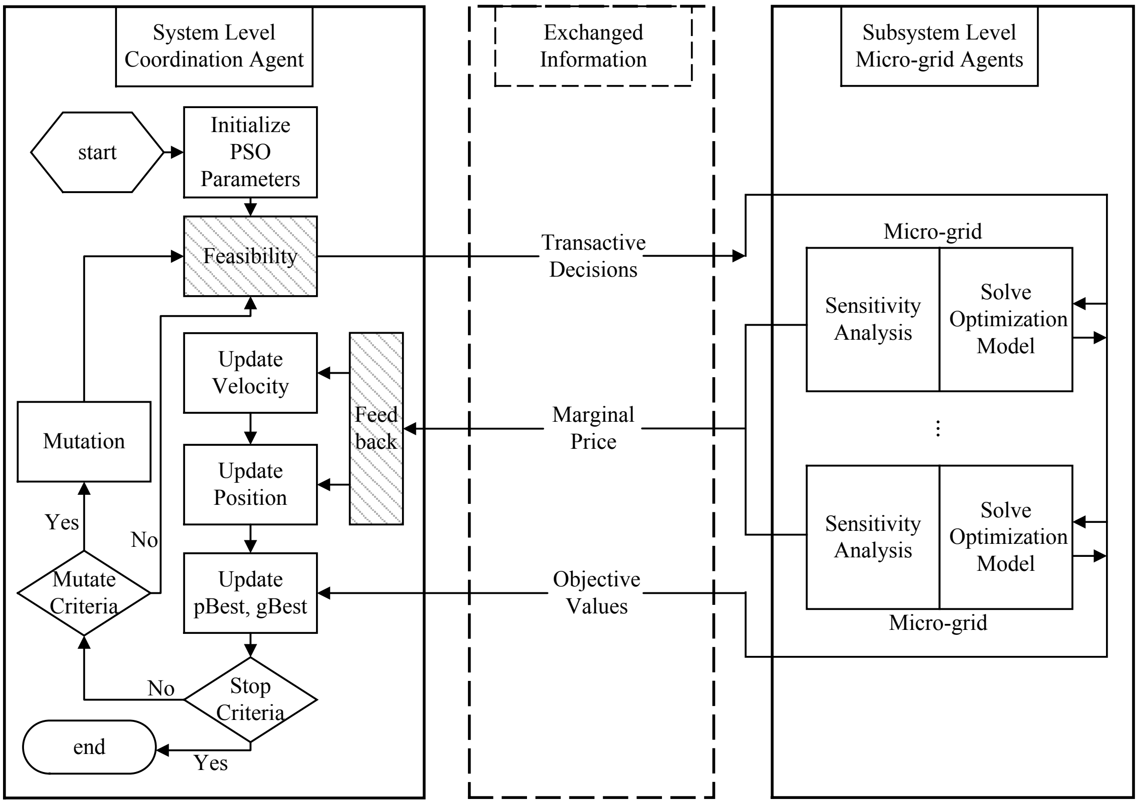


Figure 10: Marginal price based particle swarm algorithm for distributed decision making

Feasibility Module is designed to balance supply and demand of transactive energy at the system level for each time period. If the difference between total supply and total demand is not within a tolerance, random surplus of supply or demand will be assigned to a randomly selected building until it's balanced. Thus, at each iteration of MP-PSO, the transactive decision has to be checked through Feasibility Module to ensure that total supply equals to the total demand at system level, and then passed down to building agents.

Algorithm 1 Update particle velocity in feedback module

Input: $\mathbf{v}_p^{i-1}$, $\mathbf{p}_p^{i-1}$, $\mathbf{p}_g^{i-1}$, $\mathbf{eT}_p^{i-1}$, $\mathbf{mps}_p^{i-1}$
Output: vector $\mathbf{v}_p^i$ for iteration i

Update $\mathbf{v}_p^i$ using velocity equation (see Equation 3.1)
Transfer $\mathbf{v}_p^i$, $\mathbf{mps}_p^{i-1}$ into matrix $\mathbf{v}_{m,t}^{p,i}$, $\mathbf{mps}_{m,t}^{p,i-1}$
for $t = 1$ to T **do**
  Get maximum and minimum marginal prices $MaxP_{m,t}$, $MinP_{m,t}$
  Get $MidP = \big(MaxP_{m,t} - MinP_{m,t}\big)/2$
  for $m = 1$ to M **do**
    if $\left(\mathbf{mps}_{m,t}^{p,i} > MidP \text{ and } \mathbf{v}_{m,t}^{p,i} < 0\right)$ or $\left(\mathbf{mps}_{m,t}^{p,i} < MidP \text{ and } \mathbf{v}_{m,t}^{p,i} > 0\right)$ **then**
      Get a random number $r \in [0, 1]$
      $\mathbf{v}_{m,t}^{p,i} = \mathbf{v}_{m,t}^{p,i} \times (-1) \times int(r > 0.2)$
    end if
  end for
end for
Transfer matrix $\mathbf{v}_{m,t}^{p,i}$ into one dimension array $\mathbf{v}_p^i$

In the Feedback Module, two rules (see Algorithms 1 and 2) are put forward based on marginal price signal (**mps**) of supplied energy to system level from each building as evolving

Algorithm 2 Update particle position in feedback module

Input: $\mathbf{v}_p^i$, $\mathbf{eT}_p^{i-1}$, $\mathbf{mps}_p^{i-1}$

Output: vector $\mathbf{eT}_p^i$ for iteration i

1: Update $\mathbf{eT}_p^i$ using position equation (see Equation 3.2)
2: Transfer $\mathbf{v}_p^i$, $\mathbf{eT}_p^i$, $\mathbf{mps}_p^{i-1}$ into matrix $\mathbf{v}_{m,t}^{p,i}$, $\mathbf{eT}_{m,t}^{p,i}$, $\mathbf{mps}_{m,t}^{p,i-1}$
3: **for** $t = 1$ to T **do**
4:    **if** marginal prices are the same for all buildings **then**
5:       **for** $m = 1$ to M **do**
6:          Get a random number $r \in [0, 1]$
7:          $\mathbf{eT}_{m,t}^{p,i} = \mathbf{eT}_{m,t}^{p,i} \times int(r < 0.2)$
8:       **end for**
9:    **end if**
10: **end for**
11: Transfer matrix $\mathbf{eT}_{m,t}^{p,i}$ into one dimension array $\mathbf{eT}_p^i$

guidance for particles' velocity and position. The D-dimensional vector structure (e.g., position, velocity, marginal price) are transformed into the matrix forms for convenience purpose (see line 2 in Algorithms 1 and 2). It's necessary to mention that hourly marginal price signal of supplied energy (positive number as cost will intend to increase) and required energy (negative as cost will decrease) from each building are opposite numbers if no energy loss is considered. Thus only marginal price signal of supplied energy is collected here from each building for the sake of convenience in dealing with positive numbers. For each time period, if marginal price of supplied energy from one building is closer to the maximum price at this time period, generally it means it's not cost effective to make this building supplying more energy as the cost will increase more comparing with supplying same amount energy from other buildings, thus negative velocity is set to change direction with a probability of 0.8 (see lines 7-10 in Algorithm

1). In addition, if all buildings have the same marginal price, it's very likely that there won't need any more energy exchange at this time period, therefore current position is set to stay the same with a probability of 0.8 (lines 4-9 in Algorithm 2).

3.4 Case Study and Algorithm Evaluation

Due to energy crisis and environmental factors, the number of electric vehicles (EVs) or plug-in hybrid electric vehicles (PHEVs) is expected to rise considerably in near future (4). It is expected that total number of EVs will reach about 62% in 2050 in the United States (35). The city of Chicago and State of Illinois have partnered to deploy a comprehensive network of charging station infrastructure to create densest network of direct current fast charging stations in the world (102). On the other hand, building sector is responsible for more than 40% of the domestic primary energy consumption of U.S. As reviewed in Section 1.2, the potential of vehicle-to-building (V2B) integration is also a research hotspot. In the following section, distributed operation of building and charging station is used as a case to demonstrate the generality of proposed MP-PSO distributed based decision approach

3.4.1 Case Study: Building-Charging Station Cooperation*

Although lots of efforts have been made on energy systems operation for buildings, charging scheduling for EVs in charging stations or buildings network, more potential and benefits could be exploited when connecting building network and expanding charging station network. In

*This case study was previously published as: Chen, Y. and Hu, M.: A Guided Particle Swarm Optimizer for Distributed Operation of Electric Vehicle to Building Integration. Proceedings of the ASME 2017 most of the reviewed literature, centralized optimization is commonly adopted, which will be time consuming for large scale application, some existing distributed structures and algorithms are not suitable for complete autonomous operation and need more private information to be exchanged. In this case study, an integrated optimization model for a commercial building and an EV charging station is proposed to achieve more energy cost savings. Correspondingly, the performance of our proposed distributed decision approach MP-PSO (Section 3.3) is compared with two popular decomposition based distributed methods (collaborative optimization (19) and analytical target cascading (59)).

3.4.1.1 Building-Charging Station Integration and Operation Model

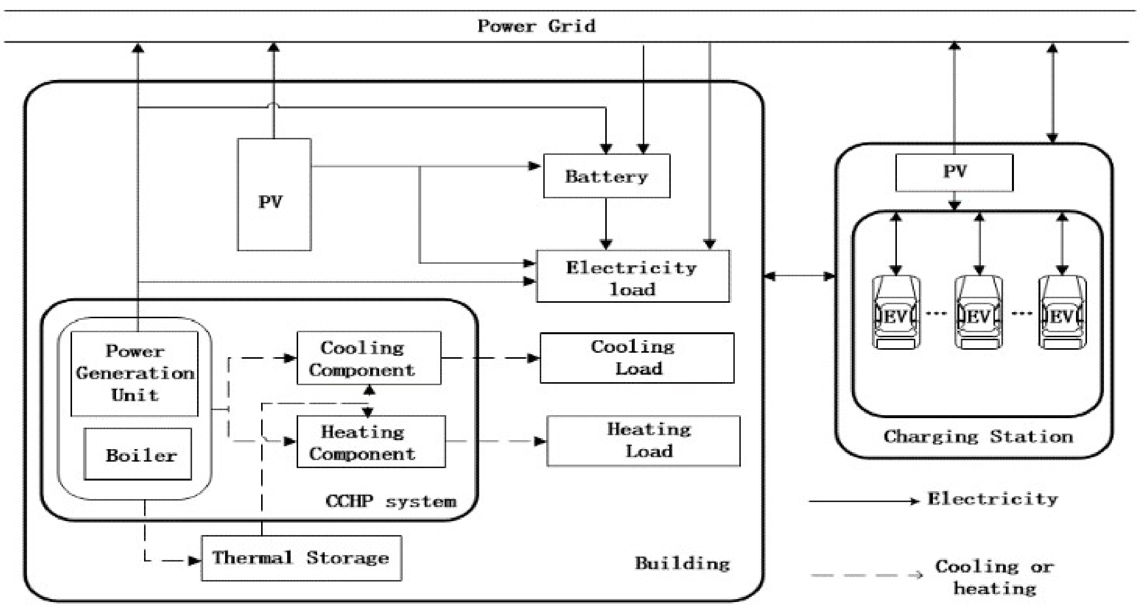


Figure 11: Overall schematic of vehicle-to-building integration with energy transaction

As shown in Figure 11, building has three modules: 1) load module which considers electricity, cooling and heating load, 2) generating module which considers solar PV panel and CCHP system, and 3) storage module which considers electric and thermal energy storage, as in Figure 5 (Section 2.2, Chapter 2). Charging station has solar PV for power generation and several charging slots to satisfy charging load from electric vehicles. Power grid is assumed to support electricity purchasing and selling while electricity energy can be freely shared between building and charging station for a higher energy efficiency. To assist the collaboration between building and charging station, a mathematical model of the collaborative operation with energy transaction is developed below.

To be concise, the mathematical model of building operation is neglected here, details could be found in Section 2.2.1, Chapter 2. The new variables, parameters for charging station operation is defined in Table VIII.

Operating Constraints for Charing Station

Operation cost for Charging Station

$$f_{CS} = \sum_t (eGP_t^{CS} \cdot PGp_t - eGs_t^{CS} \cdot PGs_t) - \sum_v FC \cdot (\widetilde{T}_v^{EV} - T_v^{EV}) \tag{3.3}$$

The operation cost of charging station consists of electricity trading fee with power grid (first term) and hourly income (e.g. parking fee, service fee) (second term).

Electricity load balance

$$eGP_t^{CS} + ePV_t^{CS} + eTin_t^{CS} = eCV_t + eGs_t^{CS} + eTout_t^{CS}, \forall t \tag{3.4}$$

TABLE VIII: Decision variables and parameters for charging station

Index for charging station	
v	Index for electric vehicles
Variables for charging station	
eGp_t^{CS}, eGs_t^{CS}	Electricity purchased from/sold back to power grid by charging station at time t
$eTin_t^{CS}, eTout_t^{CS}$	Electricity transmitted into/out charging station from/to building at time t
ePV_t^{CS}	Electricity generated by PV panel of charging station at time t
$eE_{v,t}^{EV}$	Stored energy in electric vehicle v at time t
$eEc_{v,t}^{EV}, eEd_{v,t}^{EV}$	Charging, discharging rate of energy storages of electric vehicle v at time t
$xEc_{v,t}^{EV}, xEd_{v,t}^{EV}$	Charging, discharging state of energy storages of electric vehicle v at time t
eVC_t, eCV_t	Electricity from electric vehicle fleet to CS, from CS to electric vehicle fleet at time t
Parameters for charging station	
SPV^{CS}, η_{PV}^{CS}	Size, generating efficiency of PV panel of charing station
IE_v^{EV}, ER_v^{EV}	Initial, required electricity level of electric vehicle v
SE^{EV}, sol_t	Size of storage of electric vehicles, solar radiation
$\eta_{Bc}^{EV}, \eta_{Bd}^{EV}$	Charing, discharging efficiency of electric vehicles
$\alpha_{Bmin}^{EV}, \alpha_{Bmax}^{EV}$	Coefficient for minimum, maximum storage limit of electric vehicle
$\alpha_{Bcmin}^{EV}, \alpha_{Bcmax}^{EV}$	Coefficient for minimum, maximum charging limit of electric vehicle
$\alpha_{Bdmin}^{EV}, \alpha_{Bdmax}^{EV}$	Coefficient for minimum, maximum discharging limit of electric vehicle
$T_v^{EV}, \widetilde{T}_v^{EV}$	Arrival, departure time of electric vehicle v
FC, N	Fixed cost, available charing slots in charging station

$$\textstyle\sum_v (eEc_{v,t}^{EV}/\eta_{Bc}^{EV}) \leq eCV_t, \forall t \tag{3.5}$$

$$eVC_t \leq \textstyle\sum_v (eEd_{v,t}^{EV} \cdot \eta_{Bd}^{EV}), \forall t \tag{3.6}$$

In charging station, electricity load is mainly the charging requirement of EVs. Also, in some circumstances, EVs could be discharged to power the building or sell energy back into power grid.

Constraint for PV

$$ePV_t^{CS} \leq SPV^{CS} \cdot Sol_t \cdot \eta_{PV}^{CS}, \forall t \tag{3.7}$$

Similar as Equation 2.5, electricity generation from PV panel in charging station can be estimated.

Constraints for EVs

$$xEc_{v,t}^{EV} + xEd_{v,t}^{EV} \leq 1, \forall v, t \tag{3.8}$$

$$eE_{v,1}^{EV} = IE_{v}^{EV} + (eEc_{v,1}^{EV} - eEd_{v,1}^{EV}), \forall v \tag{3.9}$$

$$eE_{v,t}^{EV} - eE_{v,t-1}^{EV} = (eEc_{v,t}^{EV} - eEd_{v,1}^{EV}), \forall v, t \geq 2 \tag{3.10}$$

$$SE^{EV} \cdot \alpha_{Bmin}^{EV} \leq eE_{v,t}^{EV} \leq SE^{EV} \cdot \alpha_{Bmax}^{EV}, \forall v, t \tag{3.11}$$

$$SE^{EV} \cdot \alpha_{Bcmin}^{EV} \cdot xEc_{v,t}^{EV} \leq eEc_{v,t}^{EV} \leq SE^{EV} \cdot \alpha_{Bcmax}^{EV} \cdot xEc_{v,t}^{EV}, \forall v, t \tag{3.12}$$

$$SE^{EV} \cdot \alpha_{Bdmin}^{EV} \cdot xEd_{v,t}^{EV} \leq eEd_{v,t}^{EV} \leq SE^{EV} \cdot \alpha_{Bdmax}^{EV} \cdot xEd_{v,t}^{EV}, \forall v, t \tag{3.13}$$

Similar as battery storage in building, the charging, discharging and stored electricity in electric storage equipped in EVs are limited by Equation 3.8 − Equation 3.13. The basic configuration (e.g. capacity, coefficient of storage limit and charging/discharging) of EVs is assumed to be the same here.

Constraints for charging schedule

$$eE_{v,t-1}^{EV} \geq ER_{v}^{EV}, \forall v, t = \widetilde{T}_{v}^{EV} \tag{3.14}$$

$$\textstyle\sum_{v}(xEc_{v,t}^{EV} + xEd_{v,t}^{EV}) \leq N, \forall t \tag{3.15}$$

$$xEc_{v,t}^{EV} + xEd_{v,t}^{EV} = 0, \forall v, t \leq T_v^{EV} ort \geq \widetilde{T}_v^{EV} \tag{3.16}$$

Equation 3.14 $-$ Equation 3.16 define the charging/discharging state of electric vehicles in the condition of their different available time and total available charging slots in charging station.

For integrated operation of building and charging station, the centralized optimization problem could be constructed and represented as Cen-Opt.

$$[\textbf{Cen-Opt}] \begin{bmatrix} min f_{cen} = f_{BU} + f_{CS} \\ s.t. Equation\ 2.2 - Equation\ 2.36 \\ Equation\ 3.4 - Equation\ 3.16 \end{bmatrix} \tag{3.17}$$

where f_{cen} is the total operation cost of building and charging station, f_{BU} is the operation cost of building (Equation 2.1). Please noted that, only electricity is allowed to be transacted between building and charging station.

3.4.1.2 Decomposition Based Distributed Operation

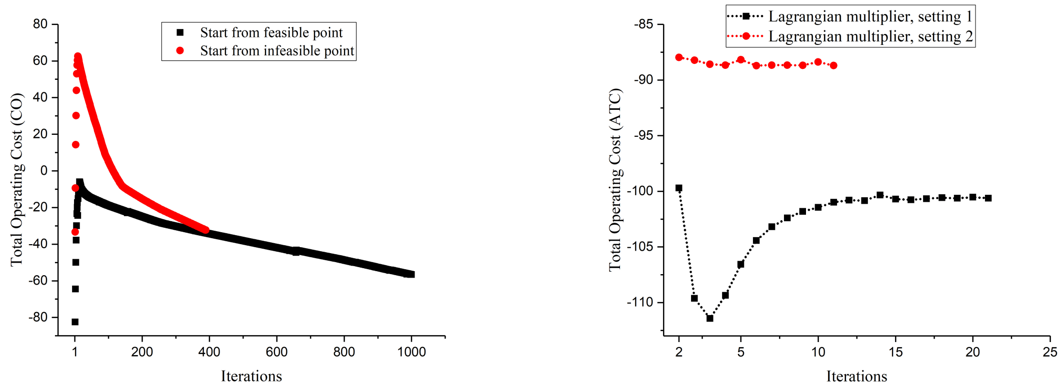
For the experiments settings, a typical medium office in Chicago climate zone is chosen for the building operation, energy load data (electricity, cooling and heating) could be collected from Ref. (24)(96). All the parameter settings about building follow the same setting as Ref. (15). For the charging station, maximum available charging slots are set to be 5 and around 10 EVs arrival for charging. Arrival time and initial stored energy of EVs are randomly generated and all departure time are set to be 6 pm with a full charging requirement. Time period of one typical day in July is considered.

For one day's operation, the optimum results of centralized optimization (model Cen-Opt Equation 3.17) is -$107.581 (with operating cost $20.19 for building and -$127.77 for charging station) while the total cost for separate operation is -$87.76 (with operating cost of $74.62 for building and -$162.39 for charging station). Thus a saving around $20 could be expected in a day when integrating building and charging station together.

For a complex optimization problem that involves several participants or stakeholders, its reasonable to decompose the complicated task into subtasks to accomplish the overall objective in a distributed way. Here, we examine two extensively adopted decomposition methods: Collaborative Optimization (CO) and Analytical Target Cascading (ATC).

The basic strategy of CO and ATC is to decompose the complex optimization into sub-optimizations at subsystem level which are linked by shared or coupling variables, and in the decision process, discrepancy between subsystem level and system level will be decreased iteratively (e.g. using penalty functions) to approach final decision (19; 79; 69; 107). In order to compare the performance of these decomposition methods and our proposed distributed approach in Section 3, standard CO in Ref. (19) and ATC with augmented Lagrangian function in Ref. (59) are conducted in this research. To keep it concise, the corresponding specific decomposition procedure and solution process of CO and ATC could be referred to Ref. (19) and (59).

To test the performance of decomposition methods, different groups of experiments are conducted based on CO and ATC decomposition structure. For CO, the solution process starts by assigning initial decisions from system level to all subsystem levels (19; 5), therefore,



(a) (b)

Figure 12: (a) Iterative process of CO, (b) Iterative process of ATC

different initial decisions based on its feasibility are chosen for this testing. For example, if the initial decisions from system level totally satisfy constraints at subsystem level then its feasible, otherwise its infeasible. Stop criteria will be triggered if these conditions are satisfied together: discrepancy between system level and all subsystem levels are less than a tolerance, absolute solution gap for continuum two iterations is less than a tolerance. Maximum iteration number is set to be 1,000 for CO. The iterative process of total system cost for CO is shown in Figure (a). For the two starting points in the first several iterations, cost from CO firstly increases due to the discrepancy coordination process between system level and subsystem level, then starts to drop eventually.

In ATC with augmented Lagrangian function (59)(69), different settings about initial Lagrangian penalty multiplier (α,β) are chosen and updated following the same procedure in Ref.

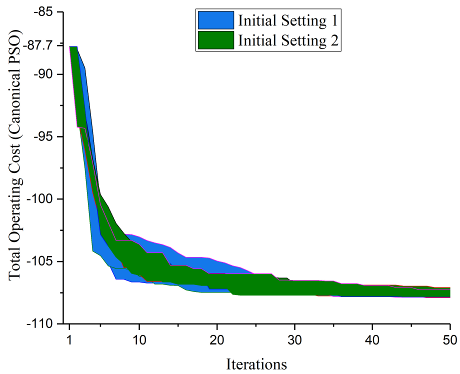
(59), the coefficient λ for updating penalty multiplier is same for the two settings (λ=1.2) which are Setting 1 (α,β) = (1, 0.8), Setting 2 (α,β) = (5, 0.1). Stop criteria for ATC consists of necessary-consistency condition and absolute gap checking. Maximum iteration number is also set to be 1,000 for ATC. The iterative process of total system cost for ATC is shown in Figure (b). Please note that, the cost of first iteration is deleted from Figure (b) because of a very large initial penalty value. Due to the penalty function in objective, total cost from ATC drops at first to decrease the penalty term and then starts to converge to the optimal solution with near-zero penalty level.

As shown, the solution seeking processes of CO and ATC largely depend on their initial settings. Also, the convergence will be a big issue as excessive copies of the shared variables have to be made to realize concurrent execution. Therefore, the two decomposition methods are more suitable and limited to lower dimensional distributed decision problems.

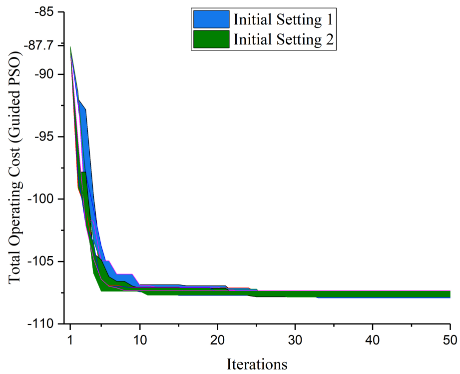
3.4.1.3 MP-PSO Based Distributed Operation

Different from the above decomposition methods, copies of shared variables wont be needed in our proposed PSO based distribution decision approach and privacy can be protected. In order to evaluate the performance, same parameter settings are applied to canonical PSO and guided PSO. The only difference is that there is no information about marginal price for canonical PSO. Similarly, two different settings about basic parameters in PSO are tested. In first initial setting, (w^0,c_1^0,c_2^0) is fixed to be (0.2, 1.1, 1.8) (Equation 3.1), thus, there will be no updating operation; in second initial setting, (w^0,c_1^0,c_2^0) is (0.6, 1.49, 1.49) initially and will be updated at each iteration i according to random generation strategy (28)(104) and nonlinear acceleration strategy (104). For each initial setting, canonical PSO and guided PSO will run five times independently. Maximum iteration number is set to be 50.

For the two versions of PSO, the filled areas for the five runs with two different initial parameter settings are shown in Figure (a) and Figure (b) respectively. Please note that the two PSOs both start from around -$87.76 (results of separate operation) because one random particle is chosen in the swarm to represent zero transactive activities between building and charging station, thus, it could make sure the swarm starts from a decision which is no worse than separate operation.



(a)



(b)

Figure 13: (a) Iterative process of canonical PSO, (b) Iterative process of guided PSO

As shown in Figure (a) and Figure (b), for both two initial settings, two versions of PSO could converge to the optimal solution for this problem. The performance of guided PSO with additional marginal price information is more stable and more effective than canonical PSO reflected by the filled areas and final iteration numbers when reaching convergence. It also could be observed from the variance for each iteration in Figure 14, for example, guided PSO has the smallest variance for both settings and converges in less ten iterations.

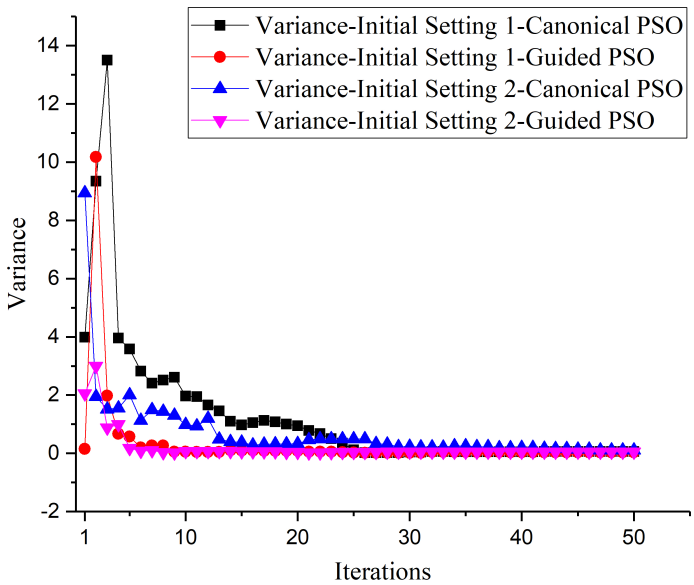


Figure 14: Variance in the iterative process

To summarize and compare all the performances, basic statistical results of the four discussed distributed operation approaches are summarized in Table IX. For all the methods, computation time is obtained by getting the max solving time from subsystem levels in each iteration and summed up together for all iterations. For the two versions of PSO, average final results, average iteration numbers and computation time when converging in the five running are presented in Table IX.

TABLE IX: Basic statistical results of conducted experiments

Methods		Iterations	Cost ($)	Time (s)
CO	Feasible point	1000	-56.62	1749
	Infeasible point	389	-32.32	672
ATC	Multiplier setting 1	22	-100.61	116
	Multiplier setting 2	12	-88.69	158
Canonical PSO	Initial setting 1	25	-107.25	1.47
	Initial setting 2	20	-107.83	1.16
MP-PSO	Initial setting 1	10	-107.69	0.81
	Initial setting 2	6	-107.85	0.96

In this case study, integration of building and charging station is proposed where energy and information can be exchanged to achieve more cost savings. To operate the vehicle to building integration more efficiently and make decisions in a distributed way, a guided PSO based distributed decision approach is proposed where marginal prices of the energy transaction decisions are utilized to guide velocity and position updating. Then, the performance of guided PSO based distributed decision approach is compared with canonical PSO and two decomposition based distributed methods. From all the experiments, guided PSO outperforms the other approaches and demonstrates stability and efficiency.

Only two decision agents are considered in the integrated operation to demonstrate the effectiveness of the marginal price guided PSO. For future research, more buildings will be included to form a community level integration, the scalability of the proposed guided PSO will be examined. Meantime, robustness of proposed algorithm will be tested based on more realistic situation by considering uncertainties from energy load and possible communication noises between system and subsystem levels.

3.4.2 Algorithm Evaluation: Effectiveness, Scalability and Robustness

In this subsection, three sets of experiments are conducted to evaluate the performances of the MP-PSO based distributed decision approach proposed in Section 3.3. In the first set of experiments, the effectiveness of the decision approach is tested firstly on distributed operation of building clusters comparing with two distributed optimization frameworks (collaborative optimization, analytical target cascading) from existing literature. With exponentially increasing of the number of buildings (from 2 to 256) in the cluster, scalability of the proposed decision approach is examined using cost saving performance and computational time performance comparing with centralized optimization in the second set of experiments. In the third set of experiments, robustness of the proposed decision approach is evaluated when communication noises exist or the energy loads of buildings are uncertain.

In this research, the centralized optimization model for building clusters is adopted from our previous study (15), and all the parameter settings are the same as in (15). The basic information of these buildings and their reference load profiles in Chicago area, U.S. can be found in (123; 92). Solar radiation for Chicago area in year 2010 is used (85). Commercial and industrial time-of-use rate from (76) is adopted for electricity purchasing price from power grid. Time period of one typical day in July is considered in this research. All the experiments are conducted on a PC with dual cores (CPU 2.00GHz and 2.50GHz) and 8GB RAM.

3.4.2.1 Effectiveness of MP-PSO based Distributed Decision Approach

In order to test the effectiveness of proposed MP-PSO based distributed decision approach for transactive operation of building clusters, the canonical PSO (CPSO) based distributed decision approach, collaborative optimization (CO) and analytical target cascading (ATC) are also studied here for comparison.

ATC was initially developed as a product development tool and works by decomposing a system into a hierarchy of subsystems and coordinating the optimization of subsystems so that the joint solution is consistent and optimal for the overall system (119; 5). ATC propagates targets using a model-based solution process, and targets are provided to design groups to work towards. If the responses from design groups cannot meet the targets or if there are consistency problems, the target propagation is revisited with new system targets and possibly more accurate analysis models (5). On the other hand, CO is distinguished by its bi-level structure and decomposes the problem along constituent disciplines, where consistency among the disciplinary subsystems is enforced via equality constraints in a system-level problem that coordinates the interdisciplinary coupling while trying to improve the system-level performance objective (5; 3; 110).

Both of these two decomposition methods have been studied and applied with respect to the distributed structure for potential parallel execution. Typically, as mentioned in Section 3.1, a distributed algorithm is proposed for security-constrained unit commitment problem based on ATC method (59). Also, a concurrent collaborative optimization technique is developed for structural optimization design (140). Based on the decomposition structure of ATC in (59; 5) and CO in (18; 5), the total system cost is calculated for all the considered optimization framework here, and compared in Table X where the number of buildings increases from 2 to 16. Summated cost of all buildings under separate operation and the optimal total system cost from centralized optimization are also listed for reference.

TABLE X: Effectiveness test for small size building clusters

# of buildings	**Separated operation**	**Centralized optimization**	**MP-PSO**	**CPSO**	**CO**	**ATC**
2	1249.41	1229.49	1227.34	1230.14	1473.55	1648.01
4	1148.23	1115.37	1117.32	1122.35	1312.86	3235.22
8	1426.85	1371.35	1377.23	1397.42	2625.41	-
16	1479.50	1395.25	1423.12	1464.35	-	-

As shown in Table X, the framework of CO and ATC fail to optimize the building clusters even when there are only two buildings participating in the transactive operation. The reasons lie in several aspects: firstly, the strategy of decomposition methods is to partition a complex system in different ways depending on the characteristic of the problem. In order to realize concurrent calculation, shared variables are usually made a lot of copies for every subsystem that sharing the variables. The solution seeking process of ATC and CO largely depends on the initial value settings of virtual shared variables passed down from system level. Secondly, due to the excessive copies, these two decomposition methods are more suitable and limited to low dimensional distributed decision problems (see Section 3.1) as convergence issue will be significant when the decision vectors are high-dimensional. For CO, the objective of each subsystem measures its discrepancy from system level and will be driven to zero by the consistency constraints at system level. In ATC, the consistency of each shared variable between parent level and children level is regularly modelled and then relaxed as a penalty function (quadratic function, exponential function and Lagrangian function, etc.) in the optimization process. Thus, the convergence difficulties are focused a lot in the reviewed relevant research.

Contrastively, different from the decomposition methods, the abovementioned problems could be avoided within our proposed bi-level modelling framework where all the possible sharing between any two subsystems are coordinated and dispatched at system level, thus distributed autonomous operation for each subsystem could be realized. And with the marginal price feedback from subsystem level, MP-PSO could allocate the sharing resources more effectively at system level. Please note that the cost of MP-PSO is slightly lower (when the number of buildings is 2) than optimal cost from centralized optimization as a result of the relative gap 0.5% defined in CPLEX. Besides the effectiveness at current problem scale, the potentials of proposed MP-PSO will be explored from different aspects in the following sections.

3.4.2.2 Scalability of MP-PSO based Distributed Decision Approach

In most state-of-the-art literature reviewed in Section 3.1 about distributed buildings operation with energy exchange, commonly adopted peer-to-peer implementation could seriously restrict the practical application at community level with a large number of possible buildings participated. As proposed for the bi-level distributed energy transaction framework, scalability of the parallel coordination algorithm - MP-PSO is examined here from the perspectives of cost saving and computational time performance.

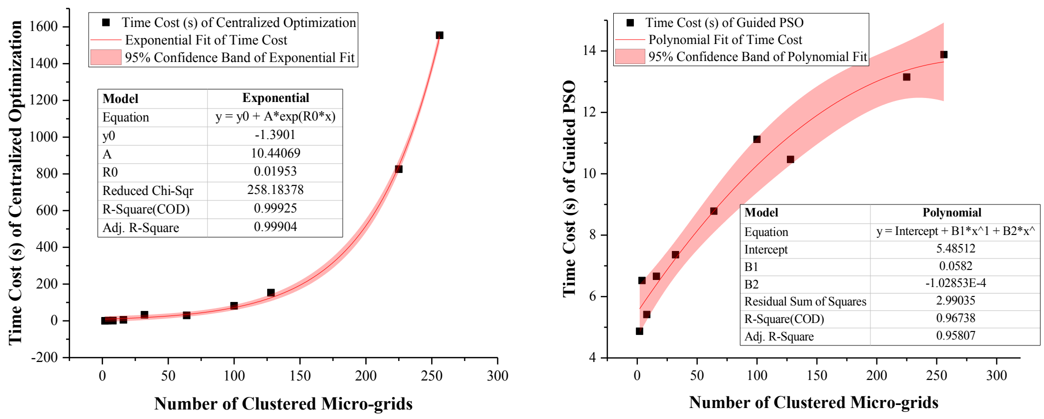
Along with the involved buildings increasing from 2 to 256, total cost of separated operation, centralized optimization, MP-PSO and CPSO are recorded in Table XI. ATC and CO are dropped here due to poor performance in previous section. In consideration of the parallelism of particles in PSO based framework, the maximum time in solving every building at subsystem level is regarded as the time consumed by each particle and the maximum time cost of all particles in particle swarm will be treated as the elapsed time for MP-PSO and CPSO at current iteration.

It can be noticed from Table XI that the performance of CPSO becomes worse as the number of buildings is equal and greater than 32. However, with the guidance of marginal price signal only, particle swarm algorithm could still hold about 32.1% (≈(23642.57 - 23206.34)/(23642.57 - 22282.26)) optimizing effect of centralized optimization in total cost saving under the circumstances of lacking all the other information at a relatively large scale of 256 buildings.

From the view of computational time performance, the time elapsed during centralized optimization and MP-PSO based decision process shown in Table XI are fitted. According to the

TABLE XI: Scalability test of large scale building clusters

# of buildings	**Separated operation**	**Centralized Optimization**		**MP-PSO**		**CPSO**	
	Cost ($)	Cost ($)	Time (sec.)	Cost ($)	Time (sec.)	Cost ($)	Time (sec.)
2	1249.41	1229.49	0.17	1227.34	4.87	1230.14	6.08
4	1148.23	1115.37	0.48	1117.32	6.52	1122.35	9.38
8	1426.85	1371.35	1.37	1377.23	5.41	1397.42	14.38
16	1479.50	1395.25	5.40	1423.12	6.66	1464.35	11.20
32	2951.23	2781.89	32.89	2876.36	7.36	2943.59	4.65
64	5890.76	5549.92	29.53	5745.60	8.78	5878.98	5.43
100	9049.92	8515.09	81.84	8858.56	11.12	9031.42	4.71
128	11796.05	11119.01	153.27	11569.37	10.47	11774.14	4.24
225	20687.83	19493.27	825.53	20296.69	13.15	20643.38	5.23
256	23642.57	22282.26	1554.33	23206.34	13.88	23593.23	5.49



(a) (b)

Figure 15: (a) Centralized optimization, (b) MP-PSO

R-Square (coefficient of determination) and Residual Sum of Squares (27), the best-fit curves are plotted with 95% confidence band in Figures 15(a) and 15(b) respectively. Indicated by the fitted curve formulation, the computation time of centralized optimization grows exponentially while that of MP-PSO falls in polynomial trend with second order. As a consequence, computational time of centralized optimization framework is extremely sensitive to problem scale in contrast to proposed distributed optimization framework. For instance, the predicted computation time of centralized framework will be more than one hour when the number of clustered buildings achieves 300.

Up to now, the conducted experiments have demonstrated the effectiveness and scalability of MP-PSO in bi-level distributed energy transaction framework comparing with centralized optimization and other decentralized optimization methods under complete certain information. However, the stochasticity within the system and from outer environment may cause great perturbation to the performance of decision framework. The ability of our proposed MP-PSO based distributed optimization framework to tolerate such uncertainties, referred to as robustness, will be evaluated next.

3.4.2.3 Robustness of MP-PSO based Distributed Decision Approach

As stated before, stochasticity from both internal and external will be considered here in order to investigate the robustness of MP-PSO based decision framework. Since marginal price signal is the only information utilized by MP-PSO based distributed optimization framework, the potential signal distortion (e.g. natural noise or intended mislead) in the communication process between system level and subsystem level will have to be paid more attention. Also, another important source of uncertainty comes from possible energy load fluctuation of some or all buildings.

To describe the uncertainty from communication process in distributed optimization framework, Gaussian noise $N(0, \sigma^2)$ is added to the original marginal price signal of energy transaction decisions ET for all particles at every iteration of MP-PSO. According to the definition of signal-to-noise ratio ($SNR = \mu/\sigma$, μ is the signal mean and σ is the standard deviation of the noise) (114) adopted here, five different uncertainty levels of SNR (here, $\sigma \in \{0.1\mu, 0.2\mu, 0.3\mu, 0.4\mu, 0.5\mu\}$) are set. Since there is no marginal price of transacted energy utilized in centralized optimization, the communication uncertainty will be directly added to the energy transaction decisions ET after being made by centralized optimization unit. Need to note that the change of energy transaction decisions ET is synchronously to the change of their own marginal price, and the range of variation is set to be $[ET \times (1 - \alpha), ET \times (1 + \alpha)]$ ($\alpha \in \{0.1, 0.2, 0.3, 0.4, 0.5\}$). On the other aspect, hourly energy load will be randomly generated from the range $[EL \times (1 - \beta), EL \times (1 + \beta)]$, where EL is original hourly energy load under deterministic circumstance and β is also assumed to have five different levels ($\beta \in \{0.2, 0.3, 0.5, 0.7, 0.9\}$), this is the same for both distributed optimization and centralized framework.

The number of clustered buildings is set to be sixteen here. Communication uncertainty and energy load uncertainty are considered for two randomly selected buildings among the sixteen and all the sixteen buildings respectively. Thus, to test the robustness against communication uncertainty, 10 groups of experiments (when communication uncertainty is considered for two selected buildings: 5 groups, represented by 2-CL1 $\sim$ 2-CL5; when communication uncertainty is considered for all sixteen buildings: 5 groups, represented by 16-CL1 $\sim$ 16-CL5) are designed for both distributed optimization framework and centralized optimization framework respectively. Similarly, 10 groups of experiments are designed to test robustness against energy load uncertainty (represented by 2-EL1 $\sim$ 2-EL5 and 16-EL1 $\sim$ 16-EL5) for these two optimization frameworks. There is also a reference group (Ref0) of experiments where no uncertainty is considered. In each group of experiment, 20 scenarios are generated based on the uncertainty level of this group.

Based on all the experimental results collected above, statistical comparison is conducted to measure the difference between populations under different uncertainty levels, and evaluate the ability of tolerating uncertainties (a.k.a. robustness) further for the two optimization frameworks. Due to the validity on small sample size (<30), Student's t-test is used here (at a 0.05 level of significance) to perform pairwise comparison among all the groups of experiments. Therefore, corresponding p-value matrix could be obtained for each two groups of experiments. Since the test of two groups are symmetrical, for the sake of conciseness, lower triangular matrix in Table XII is the p-values of t-test for MP-PSO based distributed decision approach under communication noises while upper triangular matrix is the result for centralized optimization. For example, in lower triangular part of Table XII, the p-value of group 2-CL2 and group Ref0 equals 0.02 (<0.05), which means the result difference is significant for MP-PSO with communication noise (level 2, SNR=5) added for selected 2 random buildings and without any uncertainty. Similarly, p-values of the t-test under different levels of energy load uncertainties for these two optimization approaches are presented in Table XIII for comparison.

TABLE XII: t-test for different levels of communication noises (lower triangle is p-value matrix for MP-PSO based distributed decision approach, upper triangle is p-value matrix for centralized optimization)

	Ref0	2-CL1	2-CL2	2-CL3	2-CL4	2-CL5	16-CL1	16-CL2	16-CL3	16-CL4	16-CL5
Ref0	-	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**
2-CL1	**0.033**	-	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**
2-CL2	**0.002**	0.175	-	0.481	**0.003**	**0.010**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**
2-CL3	0.231	0.602	0.113	-	**0.031**	0.056	**0.001**	**0.000**	**0.000**	**0.000**	**0.000**
2-CL4	0.275	0.382	**0.046**	0.818	-	0.935	0.452	**0.000**	**0.000**	**0.000**	**0.000**
2-CL5	0.082	0.522	**0.049**	0.948	0.704	-	0.437	**0.000**	**0.000**	**0.000**	**0.000**
16-CL1	0.085	0.574	0.062	0.916	0.678	0.953	-	**0.000**	**0.000**	**0.000**	**0.000**
16-CL2	0.113	0.671	0.101	0.879	0.663	0.900	0.943	-	**0.002**	**0.000**	**0.000**
16-CL3	**0.033**	0.973	0.163	0.618	0.393	0.540	0.593	0.691	-	**0.043**	**0.000**
16-CL4	0.067	0.975	0.215	0.654	0.455	0.612	0.655	0.730	0.998	-	**0.007**
16-CL5	0.316	0.541	0.107	0.914	0.920	0.848	0.821	0.793	0.554	0.590	-

Except self-comparisons in Table XII and Table XIII, totally 55 intergroup comparisons are proceeded for 11 columns for MP-PSO and centralized optimization separately. Then identical rate could be calculated for these 55 comparisons based on 0.05 significant level, and adopted as indicator for robustness. As it can be seen in p-value matrices, the identical rates for distributed optimization framework with communication noise and energy load variation are 0.91 ($=\frac{50}{55}$, Table XII) and 0.98 ($=\frac{54}{55}$, Table XIII) while they are 0.09 ($=\frac{5}{55}$, Table XII) and 0.96 ($=\frac{53}{55}$, Table XIII) for centralized optimization framework. It's safe to conclude that proposed MP-

TABLE XIII: t-test for different levels of energy load uncertainties (lower triangle is p-value matrix for MP-PSO based distributed decision framework, upper triangle is p-value matrix for centralized optimization)

	Ref0	2-EL1	2-EL2	2-EL3	2-EL4	2-EL5	16-EL1	16-EL2	16-EL3	16-EL4	16-EL5
Ref0	-	**0.003**	0.794	0.192	0.901	0.191	0.277	0.127	0.706	0.921	0.521
2-EL1	0.114	-	0.092	**0.020**	0.501	0.050	0.289	0.624	0.557	0.377	0.893
2-EL2	0.745	0.320	-	0.201	0.972	0.185	0.557	0.324	0.802	0.992	0.565
2-EL3	0.956	0.503	0.915	-	0.414	0.630	0.099	0.060	0.271	0.366	0.281
2-EL4	0.867	0.444	0.768	0.865	-	0.289	0.818	0.661	0.885	0.972	0.630
2-EL5	0.115	**0.043**	0.100	0.168	0.250	-	0.119	0.085	0.203	0.261	0.206
16-EL1	0.687	0.356	0.947	0.884	0.743	0.095	-	0.656	0.950	0.739	0.684
16-EL2	0.954	0.378	0.880	0.992	0.858	0.140	0.841	-	0.757	0.560	0.788
16-EL3	0.839	0.325	0.716	0.853	0.989	0.200	0.685	0.838	-	0.839	0.688
16-EL4	0.328	0.151	0.289	0.385	0.498	0.672	0.277	0.354	0.449	-	0.594
16-EL5	0.262	0.139	0.235	0.297	0.378	0.947	0.227	0.277	0.341	0.768	-

PSO for distributed optimization framework is more robust when communication noise exists in optimization process or energy load is stochastic.

3.5 Concluding Remarks

In the context of clustered buildings, energy and information can be exchanged to achieve more global benefit, such as lower energy cost, primary energy consumption and carbon emissions. Due to sharply increased computational cost in centralized optimization, several distributed algorithms have been developed in very recent research. However, the peer-to-peer topology is popularly adopted in current distributed decision framework, which is not suitable for fully parallel execution, and information sharing between stakeholders including sensitive information (e.g., energy system configuration) can't be avoided during the optimization process. In this research, we propose a MP-PSO based bi-level distributed energy transaction framework where interconnections are eliminated between any two decision making agents at subsystem level and MP-PSO is employed for overall coordination at system level. To allocate energy resources more efficiently, marginal price of transactive energy in each building is returned to system level to guide velocity and position updating for the particles. The performance of the proposed MP-PSO based distributed framework and algorithm are evaluated from three aspects of effectiveness, scalability and robustness.

CHAPTER 4

ONLINE TRANSACTIVE OPERATION FOR BUILDING CLUSTERS WITH UNCERTAINTIES

Driven by potential energy and cost savings, local buildings or micro-grids tend to form networked clusters with others for energy transaction. To enable efficient transactive operation, both centralized and distributed decision approaches are explored in the past decades. However, real-time distributed stochastic transactive operation has been less studied. To bridge the research gaps, we propose a bi-level distributed stochastic model predictive control framework to study the transactive operations of building clusters where a system level agent is employed to coordinate multiple building agents at the sub-system level. The energy transaction is optimized by a marginal price-based particle swarm optimizer at the system level. Given the energy transaction decisions, each building can independently solve a scenario-based two-stage stochastic model to optimally dispatch the electricity and ancillary services for optimal energy performance. The effectiveness of the proposed framework and coordination algorithm are demonstrated in deterministic, stochastic, and real-time operations as comparing with centralized decisions using several set of experiments. In addition, the proposed approach can realize autonomous transactive operation and be extended to community level building clusters in a plug-and-play way.

4.1 Online Operation Optimization for Building Clusters

Buildings is playing a critical role in transformation of current power grid to future smart grid. It could improve the power system economics by utilizing a variety of local generation resources, energy storage systems, and adjustable loads along with energy purchase from the main grid, and increase the reliability of local loads by ensuring an uninterrupted energy supply when the main grid power is not available (63). Centralized optimization-based scheduling approaches are popular for use in energy management systems for standalone building or interconnected buildings. For instance, popular modeling and solution approaches include mixed-integer programming (55), multi-objective optimization (109), genetic algorithm (87), benders decomposition (63), etc. To incorporate randomness, different methods are proposed to describe uncertainties. For example, stochastic programming models with risk neutral and averse options (36), scenario-based robust method for grid-connected micro-grid (138) where uncertainty is described as an uncertain set produced by interval prediction, fuzzy multi-objective optimization methods (71), probabilistic minimal cut-set-based iterative methodology for optimal planning of interconnection among micro-grids (14).

Besides centralized decision framework, distributed coordination approaches have gained more attention when multiple micro-grids could cooperate together to achieve more collective benefits. Energy trading among multiple interconnected micro-grids in a competitive market is modeled as hierarchical multileader-multifollower stackelberg game (70). Multi-layered control architecture is presented to coordinate power sharing efficiently among interconnected micro-grids (113) by optimizing operational cost of each micro-grid separately while sharing power with neighboring micro-grids whenever possible. To provide more economic operation options, it is suggested that adjustable power should also be informed to community energy management in addition to surplus and shortage information (12). Robust distributed control strategy is proposed for power exchanging of cooperating micro-grids (10) based on partially nested information to minimize the maximum divergence from an agreed power exchange among micro-grids. A bi-level optimal control scheme is proposed for stochastic optimal operation of interconnected micro-grids where lower level decision makers (or micro-grids) solve a stochastic optimization problem following available information at local level and references from upper level (83).

To further decrease model complexity of planning optimization and utilize updated information, model predictive control (MPC) or rolling horizon control approaches have also been proposed for building or micro-grid energy management. A hierarchical outage management scheme is proposed in (37), micro-grids schedule their available resources in first stage using MPC-based algorithm and then distribution system operator coordinates possible power transfers among micro-grids in second stage. In a two-layer MPC method for island micro-grid operation (112), first layer presents an optimal control for energy dispatch, to improve robustness toward prediction errors, a boundary value problem is solved to adjust diesel generator power in second layer. A stochastic-predictive energy management system for isolated micro-grid is proposed (93) where unit commitment variables (first stage decisions) are determined by solving stochastic mixed-integer linear programming model and optimal power flows (second stage decisions) are refined using a nonlinear programming formulation. The optimal control problem of coupled micro-grids is modeled as a decentralized partially-observable Markov decision process (135) where a look-ahead dual multiplier-based decentralized control mechanism is proposed using centralized information. A three-stage MPC-based decision framework is developed for energy sharing under uncertainty (48), including decisions generation stage, decision execution stage and data fusion-based prediction calibration stage.

As reviewed, sizeable research has been conducted for optimal scheduling problem of buildings using centralized approaches, distributed approaches and online optimization, several issues still need to be addressed including topology issue and coordination issue. Peer-to-peer connection topology (98) is commonly adopted for power exchange in current literature, however, the complexity will increase exponentially along with number of involved buildings and thus such topology is not scalable for large scale application. In addition, some distributed coordination algorithms (70) are actually sequential process and usually too much energy system information has to be shared in coordination which is not favorable for privacy protecting and will burden communication network. To address these issues, scalable network topology and parallel coordination algorithm are focused in this research. Contributions of this research can be summarized from three aspects: 1) a two-stage stochastic model is developed for centralized transactive operation of building clusters where electricity and ancillary services are simultaneously optimized, 2) a bi-level distributed energy transaction framework is proposed to enable real-time stochastic model predictive control which transforms the peer-to-peer structure into the hierarchical structure, and a decision problem involving multiple agents can be implemented with fewer concern of the scalability issue, and 3) a novel marginal price-based coordination algorithm using particle swarm optimizer is employed at system level to balance energy transactive decisions which significantly reduces the amount of information shared among buildings.

4.2 Stochastic Operation Model for Building Clusters

Centralized model is firstly established as a basic reference for optimal operation strategy of building clusters where information and energy (only electricity is considered for now) could be exchanged freely to achieve more collective interests. Without loss of generality, each building is assumed to have six modules (15): 1) two load modules: electricity and thermal load (cooling and heating), 2) two generating modules: PV and CCHP system, and 3) two storage modules: battery and thermal storage. Power grid is assumed to support electricity purchasing and selling for buildings, and different operating reserve services (20) could be provided by CCHP system and battery, and sold into ancillary market. All the variables and parameters are defined in Table XIV

4.2.1 Two-stage Stochastic Model

At the first stage, all discrete control decisions (here-and-now) have to be made before the uncertainty of input random variables is realized. The uncertain variables include electricity loads and solar radiation level in the study horizon. These uncertainties are represented using scenario-based sampling techniques. In the second stage, continuous dispatch decisions (wait-and-see) are generated.

Objective Function:

$$f_{cost}^{Total} = \sum_s Pr_s \cdot (f_{cost}^{O} + f_{cost}^{E} - f_{prof}^{R}) \tag{4.1}$$

TABLE XIV: Decision variables and parameters for Stochastic Model

Indices	
n, s, t	Index for buildings, scenarios, time
$CCHP$	Combined cooling, heating, power system
GU, BO	Power generating unit, boiler in $CCHP$
CP, HP	Cooling, heating component in $CCHP$
BS, TS, PV	Battery, thermal storage, solar panel
Parameters for stochastic model	
δ, S	Efficiency, size of different energy systems
Pp, Ps, Fp	Price of electricity purchasing, selling, fuel
Pur, Pdr, Pnr	Price for three kinds of operating reserves
$CE, Ctax$	Emission conversion factors, carbon tax
$\widetilde{EL}, \widetilde{SR}$	Stochastic electric load and solar radiation
CL, HL	Cooling, heating load for buildings
SE, IE	Size and initial level of energy storages
a, b	Fuel-to-electricity conversion parameters
η_c, η_d, η_l	Charging, discharging, line efficiency
$\overline{\alpha}, \underline{\alpha}$	Coefficient of max, min storage limit
$\overline{\alpha}_c, \underline{\alpha}_c$	Coefficient of max, min charging rate
$\overline{\alpha}_d, \underline{\alpha}_d$	Coefficient of max, min discharging rate
$\overline{\alpha}_{GU}, \underline{\alpha}_{GU}$	Coefficient of max, min generating rate
QPD, QSC	Quick start discharging, generating rate
$MUSR, MDSR$	Max upward, downward spinning limit
Variables for stochastic model	
ep, es	Electricity purchased, sold to power grid
eTi, eTo	Electricity transmitted in and out
fGU, fBO	Fuel consumed by GU, BO in $CCHP$
eGU, ePV	Electricity generated by GU, PV
qTC, qTH	Thermal energy from TS to CP, HP
qCT, qCC, qCH	Thermal from $CCHP$ to TS, CP, HP
eE, eEc, eEd	Stored energy, charging, discharging rate
usr, dsr, nsr	Spinning up, down, non-spinning reserve
$\overline{pg}, \underline{pg}$	Max, min available capacity of GU
$\overline{eEc}, \underline{eEc}$	Max, min available charging rate
$\overline{eEd}, \underline{eEd}$	Max, min available discharging rate
xEi, xEo	IN/OUT state of electricity transaction
xGU, xEc, xEd	ON/OFF, charging, discharging state

$$f_{cost}^{O} = \sum_{n,t}(ep_{s,n,t} \cdot Pp_t - es_{s,n,t} \cdot Ps_t) + \sum_{n,t}(fGU_{s,n,t} \cdot Fp_t + fBO_{s,n,t} \cdot Fp_t) \tag{4.2}$$

$$f_{cost}^{E} = \sum_{n,t}(ep_{s,n,t} \cdot CE^{PG} + fGU_{s,n,t} \cdot CE^{GU} + fBO_{s,n,t} \cdot CE^{BO}) \cdot Ctax \tag{4.3}$$

$$f_{prof}^{R} = \sum_{n,t}[(usr_{s,n,t}^{CCHP} + usr_{s,n,t}^{BS}) \cdot Pur + (dsr_{s,n,t}^{CCHP} + dsr_{s,n,t}^{BS}) \cdot Pdr + (nsr_{s,n,t}^{CCHP} + nsr_{s,n,t}^{BS}) \cdot Pnr] \tag{4.4}$$

In this research, total system cost of building clusters is the objective to be minimized which consists of system operation cost f_{cost}^{O}, carbon emission cost f_{cost}^{E} and profit made by selling reserve services into ancillary market f_{prof}^{R}.

Constraints:

1) Electricity load balance

$$ep_{s,n,t} + ePV_{s,n,t} + eGU_{s,n,t} + eEd_{s,n,t}^{BS} \cdot \eta_d^{BS} + eTi_{s,n,t} \cdot \eta_l = \widetilde{EL}_{s,n,t} + es_{s,n,t} + \frac{eEc_{s,n,t}^{BS}}{\eta_c^{BS}} + eTo_{s,n,t} \tag{4.5}$$

2) Thermal load balance

$$(qCC_{s,n,t} + qTC_{s,n,t}) \cdot \delta^{CP} = CL_{n,t} \tag{4.6}$$

$$(qCH_{s,n,t} + qTH_{s,n,t}) \cdot \delta^{HP} = HL_{n,t} \tag{4.7}$$

3) Constraint for PV

$$ePV_{s,n,t} \le S_n^{PV} \cdot \widetilde{SR}_{s,t} \cdot \delta^{PV} \tag{4.8}$$

4) Constraint for CCHP

a) Fuel consumption constraints

$$fBO_{s,n,t} \leq S_n^{BO} \tag{4.9}$$

$$fGU_{s,n,t} \leq S_n^{GU} \cdot xGU_{n,t} \tag{4.10}$$

b) Electricity generation constraints

$$eGU_{s,n,t} \leq \frac{(fGU_{s,n,t} - b_{GU} \cdot xGU_{n,t})}{a_{GU}} \tag{4.11}$$

$$\begin{aligned} S^{GU} \cdot \underline{\alpha}_{GU} \cdot xGU_{n,t} \leq \underline{pg} \leq eGU_{s,n,t} \\ \leq \overline{pg} \leq S^{GU} \cdot \overline{\alpha}_{GU} \cdot xGU_{n,t} \end{aligned} \tag{4.12}$$

c) Thermal generation constraints

$$qCT_{s,n,t} \leq S_n^{TS} \tag{4.13}$$

$$eEc_{s,n,t}^{TS} \leq qCT_{s,n,t} \cdot \eta_c^{TS} \tag{4.14}$$

$$qTC_{s,n,t} + qTH_{s,n,t} \leq eEd_{s,n,t}^{TS} \cdot \eta_d^{TS} \tag{4.15}$$

$$qCT_{s,n,t} + qCC_{s,n,t} + qHC_{s,n,t} \leq fGU_{s,n,t} \cdot \delta^{GU} + fBO_{s,n,t} \cdot \delta^{BO} \tag{4.16}$$

5) Constraints for battery and thermal storage

$$xEc_{n,t} + xEd_{n,t} \leq 1 \tag{4.17}$$

$$eE_{s,n,1} = IE + (eEc_{s,n,1} - eEd_{s,n,1}) \tag{4.18}$$

$$eE_{s,n,t} - eE_{s,n,t-1} = eEc_{s,n,t} - eEd_{s,n,t} \tag{4.19}$$

$$SE \cdot \underline{\alpha} \leq eE_{s,n,t} \leq SE \cdot \overline{\alpha} \tag{4.20}$$

$$SE \cdot \underline{\alpha}_c \cdot xEc_{n,t} \leq \underline{eEc}_{s,n,t} \leq eEc_{s,n,t} \leq \overline{eEc}_{s,n,t} \leq SE \cdot \overline{\alpha}_c \cdot xEc_{n,t} \tag{4.21}$$

$$SE \cdot \underline{\alpha}_d \cdot xEd_{n,t} \leq \underline{eEd}_{s,n,t} \leq eEd_{s,n,t} \leq \overline{eEd}_{s,n,t} \leq SE \cdot \overline{\alpha}_d \cdot xEd_{n,t} \tag{4.22}$$

This group of constraints should be applied to both battery and thermal storage.

6) Constraint for reserve service

a) Reserve provided by battery storage

$$dsr^{BS}_{s,n,t} \leq (\overline{eEc}^{BS}_{s,n,t} - eEc^{BS}_{s,n,t}) + (eEd^{BS}_{s,n,t} - \underline{eEd}^{BS}_{s,n,t}) \tag{4.23}$$

$$usr^{BS}_{s,n,t} + nsr^{BS}_{s,n,t} \leq (eE^{BS}_{s,n,t} - SE^{BS} \cdot \underline{\alpha}^{BS}) + (eEc^{BS}_{s,n,t} - \underline{eEc}^{BS}_{s,n,t}) + (\overline{eEd}^{BS}_{s,n,t} - eEd^{BS}_{s,n,t}) \tag{4.24}$$

$$usr^{BS}_{s,n,t} + nsr^{BS}_{s,n,t} \leq SE^{BS} \cdot QPD \cdot (1 - xEc^{BS}_{n,t} - xEd^{BS}_{n,t}) + (eEc^{BS}_{s,n,t} - \underline{eEc}^{BS}_{s,n,t}) + (\overline{eEd}^{BS}_{s,n,t} - eEd^{BS}_{s,n,t}) \tag{4.25}$$

b) Reserve provided by CCHP

$$dsr_{s,n,t}^{CCHP} \leq eGU_{s,n,t} - \underline{pg} \tag{4.26}$$

$$dsr_{s,n,t}^{CCHP} \leq S^{GU} \cdot MDSR \cdot xGU_{n,t} \tag{4.27}$$

$$usr_{s,n,t}^{CCHP} + nsr_{s,n,t}^{CCHP} \leq \overline{pg} - eGU_{s,n,t} \tag{4.28}$$

$$\begin{aligned} usr_{s,n,t}^{CCHP} + nsr_{s,n,t}^{CCHP} \leq S^{GU} \cdot MDSR \cdot xGU_{n,t} \\ + S^{GU} \cdot QSC \cdot (1 - xGU_{n,t}) \end{aligned} \tag{4.29}$$

More details of modeling reserve service of battery and CCHP can be found in reference (20).

7) Constraints for local transaction market

$$eTi_{s,n,t} \leq xEi_{n,t} \cdot M \tag{4.30}$$

$$eTo_{s,n,t} \leq xEo_{n,t} \cdot M \tag{4.31}$$

$$xEi_{n,t} + xEo_{n,t} \leq 1 \tag{4.32}$$

$$\textstyle\sum_n eTi_{s,n,t} = \sum_n eTo_{s,n,t} \tag{4.33}$$

Transmitted electricity depends on the mutually exclusive transmission IN/OUT states, and it should be balanced. Electricity transaction will not be allowed in the cluster if transmission states are all set to be 0, which is equivalent with conducting optimization for all building agents separately. M is a large number.

4.2.2 Scenario Sampling and Reduction

Simulating random variables requires generation of appropriate values in accordance with their respective probability distributions. Taking energy load sampling as an instance, without loss of generality, we assume that hourly electricity load of each building is a random variable that follows normal distribution $\mathbf{x}_t \sim N(\mu, \sigma^2)$, and thus, electricity load for a sample period T (i.e. 24 hours) follows multivariate normal distribution $\mathbf{X} = [x_1, x_2, \ldots, x_T] \sim N_T(\boldsymbol{\mu}, \boldsymbol{\Sigma})$, μ is a T-dimensional mean vector, and $\boldsymbol{\Sigma}$ is a $T \times T$ covariance matrix. $\boldsymbol{\mu}$ and $\boldsymbol{\Sigma}$ could be obtained from historical data. The process is similar for solar radiation sampling.

To achieve computation tractability while capturing the main stochastic information of random distribution embedded in the original scenario set as much as possible, simultaneous backward method (91) is implemented to trim down the number of deteriorated scenarios. 1000 scenarios are sampled initially and will be reduced to different numbers based on the reduction algorithm.

TABLE XV: Result comparison of different scenarios (with energy transaction)

# of scenarios	Mean	SD	CI (95%)	RE (%)	CV (%)	Expected Objective	VSS
20	1773.91	45.11	19.77	1.06	0.56	1857.93	445.38
40	1772.13	38.63	11.97	0.64	0.34	1869.67	424.03
60	1772.69	35.55	8.99	0.47	0.25	1877.21	406.71
80	1775.96	36.44	7.98	0.42	0.22	1884.82	411.03
With energy transaction - optimal deterministic solution: 1664.92							

TABLE XVI: Result comparison of different scenarios (without energy transaction)

# of scenarios	**Mean**	**SD**	**CI (95%)**	**RE (%)**	**CV (%)**	**Expected Objective**	**VSS**
20	2260.84	64.93	28.45	1.20	0.64	2361.84	146.23
40	2262.49	52.23	16.18	0.68	0.36	2372.15	140.94
60	2266.29	47.97	12.14	0.51	0.27	2378.41	142.19
80	2268.12	48.95	10.72	0.45	0.24	2383.22	141.00
Without energy transaction - optimal deterministic solution: 2008.38							

Coefficient of variation (CV) (91) $cv_f = \frac{\sigma_f}{\mu_f \sqrt{N_s}}$ is utilized to determine whether the estimation seems to be accurate enough and stop scenarios trimming process, where σ_f and μ_f are the standard deviation and mean values of the output random variable f, respectively. If the value of cv_f is less than a pre-specific tolerance (i.e. between 0.1% and 1%, 0.25% is used here), then the outcomes can be considered as acceptable results and number of scenarios can be determined (See Table XV and Table XVI). The other indexes such as Mean, Standard Deviation (SD), 95% Confidence Intervals (137), Relative Error, Expected Objective, and the Value of Stochastic Solution (VSS) (33) for different inducted number of scenarios are also calculated. The value of Mean and SD comes from statistics of all objective values after solving stochastic model deterministically for each single scenario, and Expected Objective is the optimal objective value of two-stage stochastic model. To evaluate the benefit of using stochastic programming over deterministic model, VSS has been widely used in related literature. It is an indicator of the impact of uncertain variables on the solution (33). Indicated by a much larger VSS, it's more necessary to adopt stochastic programming approach when energy could be transacted among buildings.

4.3 Distributed Stochastic MPC and Algorithms

In centralized stochastic model developed for networked building clusters, the only interaction among all building agents is their possible electricity transaction (eTi,eTo). To avoid sharply increased computational cost, a bi-level distributed decision framework is employed, in which transaction decisions are made at the system level and all building agents at the subsystem level could optimize its own operations autonomously, see Figure 7.

Different from most of the existing approaches, our proposed distributed energy transaction framework has three main advantages: 1) autonomous operation can be realized for participated buildings at the subsystem level in a real parallel way, 2) comparing to fully connected (peer-to-peer) structure, it can be easily expanded with more buildings joining or dis-joining the cluster, 3) private information (e.g. load profile, energy system configuration, etc.) of each building can be protected during the cooperation process. Online MPC approach could be embedded within the proposed bi-level distributed decision framework. In MPC, the optimization problem could be solved for a sequence of control actions over the whole finite horizon at each time step and only the decisions for next time step is implemented. The use of MPC considers the impact of future conditions on the present operation of the buildings, and accounts for the uncertainty of input data (forecasts of load and solar radiation) by continuously updating the optimal dispatch based on most recent available information (93).

The stochastic MPC approach can be integrated with proposed bi-level distributed decision framework according to the following procedures:

(i) before current time step t, sample uncertainty for future horizon window $t + w$, reduce scenario number to desirable level;

(ii) solve stochastic optimization problem for time dimension $t + w$ using the proposed bi-level decision framework;

(iii) fix first-stage control variable, solve corresponding deterministic model when the information become certain in time step t;

(iv) obtain energy level of battery and thermal storage in time step t which are used as inputs for next iteration in $t + 1$;

(v) repeat (i) $-$ (iv) until the last time step.

4.3.1 Swarm Intelligence Based Coordination Algorithm

To serve the purpose of balancing transaction decisions at the system level and protect sensitive information for each building agent, a guided particle swarm optimizer (PSO) is designed and proposed by adopting the concept of marginal price which plays a crucial role to support decision making in managerial economics. In our case, the hourly marginal price of energy transaction decisions will be collected, then this information will be used to guide velocity and position updates in the expectation of more stable and effective performance. The overall process flow of proposed stochastic MPC for transactive operation is shown in Figure 16.

Three stages are included in proposed stochastic MPC process: (1) Prediction Stage: uncertainties about energy load and solar radiation level in near future are simulated by scenarios sampling and modeled by two-stage stochastic programming. Details of step 1 and 2 are explained in Section **??**; (2) Guided PSO Stage, the guided PSO is mainly designed to efficiently

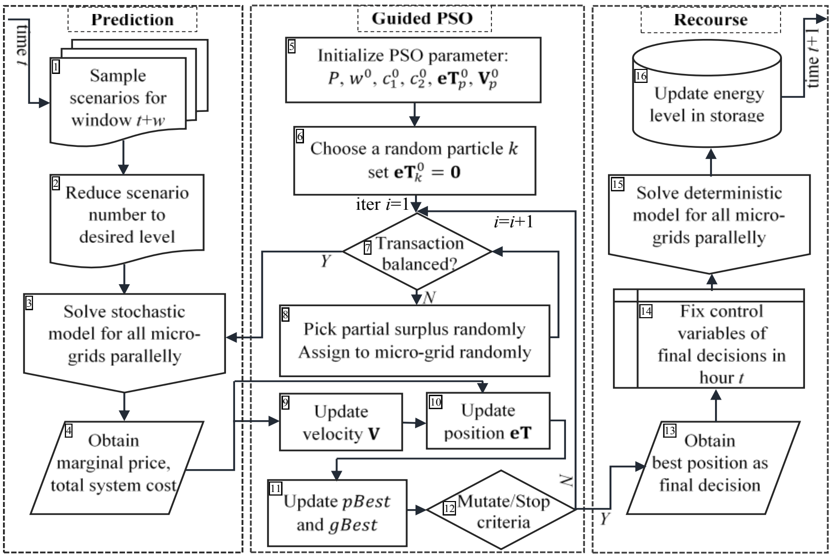


Figure 16: Overall process flow of the proposed stochastic MPC for transactive operation

solve two-stage stochastic model proposed in the Prediction Stage in a distributed way; (3) Recourse Stage, here-and-now decisions (control variables) from Prediction Stage will be applied and corresponding deterministic operation model will be optimized after the uncertainties are realized.

In step 5, swarm size P, learning factors c_1, c_2 and inertia weight w are initialized and will be adjusted in each iteration i according to nonlinear acceleration strategy (103) and random generation strategy (29) separately. Real number encoded particle is used to represent energy transaction decisions and the fitness of the particle is the total system cost. Since the transmitted energy eTi and eTo cannot exist simultaneously, they can be represented by only one D-dimensional position vector ($\mathbf{eT}$) (positive number will be assigned to eTi, absolute value of negative number will be assigned to eTo). In step 6, a random particle k is chosen as reference particle where its position is set to be $\mathbf{0}$, which means there is no cooperation or electricity transaction among all building agents. By doing this, a better cooperative solution can be guaranteed in iterative small fitness-picking process.

Then steps 7 and 8 are designed to balance transactive energy at the system level for each time period to maintain the solution feasibility. If the difference between supply and demand is not within a tolerance, random surplus of supply or demand will be assigned to random decision agent (building) until it's balanced. Balanced transaction decisions are evaluated by solving stochastic model in step 3 using mature mixed integer programming (MIP) engine. In the first iteration, the decisions about hourly purchasing and selling electricity from and to power grid (ep and es) based on the reference particle are used as new upper and lower boundaries of position vector $\mathbf{eT}$. In this way, energy transaction decisions of PSO could be limited in a most reasonable range defined by non-cooperative solution since the building will not provide energy for other buildings in the cooperative operation if it doesn't have surplus energy sold back to power grid in non-cooperative operation.

Hourly marginal prices of energy transaction decisions (or position vector $\mathbf{eT}$), byproduct of solving stochastic model in step 3, are collected in step 4. Two rules are put forward as evolving guidance for velocity and position update of particles in designed feedback function (steps 4, 9 and 10). For each time period, when the marginal price is positive, then a higher marginal price generally means it's not cost effective to let this decision agent supply more energy as the cost will increase more comparing with supplying same amount energy from other decision agents, thus negative velocity is set to change direction with a high probability. In addition, if all decision agents have the same marginal price, it's very likely that there won't need any more energy exchange at this time period, therefore current position is set to stay the same with a high probability. Individual best position and global best position are updated in step 11. Different mutation/stop criteria could be designed in step 12.

In Recourse Stage, first stage decision variables (control variables) of global best solution in current time t is fixed and the corresponding deterministic models are solved distributively after uncertainties are realized in this hour t. At last, stored energy levels in BS and TS are updated for the next period of model predictive control.

4.4 Distributed Stochastic Online Experiments

In this subsection, sets of experiments are conducted to evaluate and compare the performance of proposed distributed approaches under different conditions. Three commercial buildings (Large Office, Primary School and Hospital) in Chicago climate zone are chosen, energy load data (electricity, cooling and heating) and other parameter settings (i.e. electricity price, fuel price, etc.) follow the same setting as in (15; 20). Time period of one typical day in July is considered in this research. All experiments are conducted on the same workstation under same system settings.

4.4.1 Day-ahead Transactive Operation

Day-ahead transactive operation without uncertainties is firstly considered. Under this circumstance, the steps 1 and 2 in the Prediction stage, and the Recourse stage are not needed (see Figure 16). Step 3 will be "Solve deterministic model for all buildings parallelly". When uncertainties are included in day-ahead transactive operation, step 1 in Figure 16 needs to sample scenarios for 24 hours. After the uncertainties are realized, which we assume the expected values of all random variables (solar radiation and electricity load) in each hour consist of the realized scenario, the first stage control variables are fixed to solve day-ahead deterministic models.

Centralized optimization framework is used as comparison reference for all experiments. Thus, based on different optimization frameworks (Cen: Centralized, Dis: Distributed), taking uncertainties into account or not (Det: Deterministic, Sto: Stochastic), whether electricity transaction is allowed among buildings or not (Tran: with transaction, Ntran: without transaction), totally six different possible optimization approaches are constructed and solved for day-ahead transactive operation. Due to the nature of swarm intelligence, the best and worst cases (W: Worst, B: Best) have been chosen out of five continuous runs. According results are recorded in Table XVII, relative gap tolerance of MIP engine in CPLEX is set to be 0.001. Stop criteria for guided PSO is set based on the improvement of fitness value in ten successive iterations.

In term of objective value, Approach A and C serve as the upper and lower bounds of Approach B because of step 6 in Figure 16, Similarly, Approach D and F bound Approach E. The computation time grows dramatically for scenario-based stochastic approaches as the number of variables explodes along with the number of scenarios. Please note that, in consideration of the parallelism of particles in PSO algorithm, the maximum time in solving every building at subsystem level is regarded as the time consumed by each particle and the maximum time

TABLE XVII: Day-ahead transactive planning using different optimization approaches

Approach	**Objective**	**Iterations**	**Time (s)**
(A) Cen-Det-Ntran	2008.38	–	3.79
(B) Dis-Det-Tran	(W) 1735.40	22	12.72
	(B) 1688.29	40	29.15
(C) Cen-Det-Tran	1664.92	–	3.20
(D) Cen-Sto-Ntran	2075.71	–	4478.50
(E) Dis-Sto-Tran	(W) 1875.64	30	21898.91
	(B) 1815.42	33	24430.57
(F) Cen-Sto-Tran	1736.60	–	>34238.06

cost of all particles in swarm is treated as the elapsed time at current iteration. The time for distributed approach B and E in Table XVII are the time summation over all iterations.

The only information shared in proposed coordination algorithm is marginal price of transactive decisions, which could reflect potential change on objective value given extra unit of energy. Hourly marginal price is a single value but contains comprehensive system information in current state. To illustrate the relationship between hourly marginal price ($e\dot{T}i$, $e\dot{T}o$) of transaction variable (eTi, eTo) and electricity transaction, the original marginal price when there are no transaction among buildings (Figure 17) and the optimal electricity transaction results if transaction is allowed (Figure 18) are shown for deterministic situation. Economically speaking, the marginal price (or marginal cost) equals to the extra cost of producing extra unit of product (first derivative). In this sense, $e\dot{T}i \leq 0$, $e\dot{T}o \geq 0$ and the absolute value $|e\dot{T}i| = e\dot{T}o$ if line loss is not included in electricity load balance. However, with line coefficient η_l in the model, the hourly marginal prices satisfy $|e\dot{T}i| + 0.001 = e\dot{T}o$ in our case. It needs to be emphasized that hourly $e\dot{T}o$ changes along with hourly decision eTo because of marginal effect.

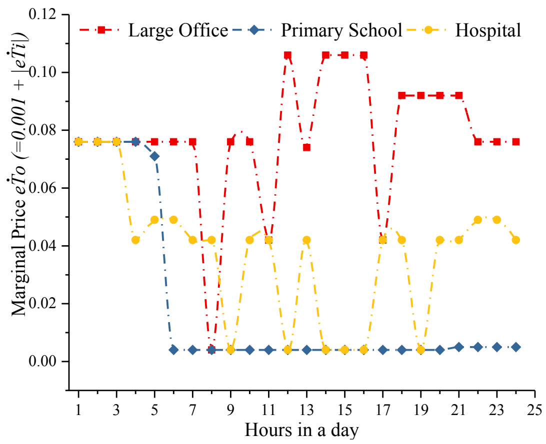


Figure 17: Hourly marginal price without transaction

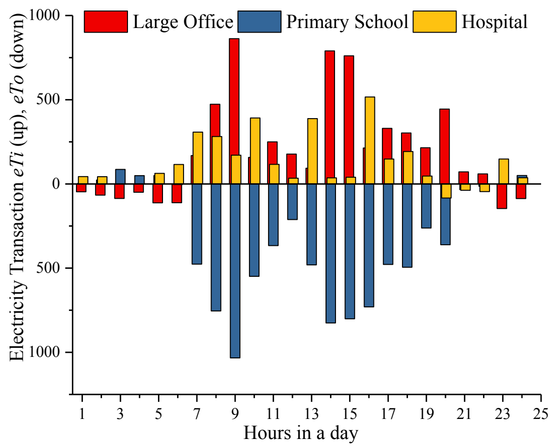


Figure 18: Centralized optimal electricity transaction

It is observed from Figure 17 that, when there is no energy transaction (set $eTi = eTo = 0$), hourly marginal prices ($e\dot{T}o$) have the trend Large Office > Hospital > Primary School, which means that, if energy transaction is allowed, the cost of Large Office will increase more than Hospital and much more than Primary School by providing same amount of electricity under current situation, and on the other side, the total system cost has more potential to be lower if transferring electricity from Primary School to Large Office. The centralized optimal transaction results in Figure 18 have backed up this viewpoint. However, the rigorous transaction amount is limited by many other factors together like the capacity of their energy systems, available renewable energy, etc.

By utilizing marginal price information, guided PSO performs more effectively with less iterations and more stable than canonical form of PSO (17). Comparing with centralized optimization framework, the private information of energy systems configuration will not be shared within the proposed distributed framework, and the computational cost could be decreased via parallel computing, especially when more buildings are involved.

4.4.2 Stochastic MPC for Transactive Operation

Indicated by the results of stochastic day-ahead planning in Table XVII, the computational costs are extremely high due to uncertainty samplings which makes it not suitable for transaction operating at real-time scale. In this subsection, our proposed stochastic MPC decision process is implemented to make real-time transaction decisions.

Based on the accuracy of predicted information for time window $t + w$ (current time step t), three modes of MPC are recognized here: 1) MPC with prefect prediction, prediction is assumed to be perfectly accurate in this mode, 2) MPC with next-hour calibration, comparing with mode 1), calibration is conducted for each time step t, and thus information in time step t is assumed to be accurate (only one scenario) after calibration but stochastic for time window w; 3) MPC with stochastic prediction, in this mode, the uncertainties are sampled for time window $t + w$. Different prediction length (1 hour, 4 hours and 8 hours) are tested for each mode. Maximum prediction length of 8 hours is chosen for comparison in consideration of the balance between objective improvement and computation cost. Results from centralized and distributed optimization approaches are recorded for each mode in Table XVIII, Table XIX, Table XX. Since MPC process needs to iterate through and update each hour of one day iteratively, the max iteration number and max elapsed time in all 24 time periods of MPC are focused.

TABLE XVIII: Transactive operation using stochastic MPC with perfect prediction

Approach	**Prediction**	**Objective**	**Max Iters**	**Max Time (s)**
(A) Cen-Sto-Ntran	1 h	2183.64	–	0.05
	4 h	2127.48	–	0.16
	8 h	2102.54	–	0.92
(B) Dis-Sto-Tran	1 h	(W) 1954.10	10	1.59
		(B) 1953.44	10	1.10
	4 h	(W) 1891.14	10	1.56
		(B) 1883.77	12	1.43
	8 h	(W) 1888.27	14	4.17
		(B) 1834.08	14	4.54
(C) Cen-Sto-Tran	1 h	1954.73	–	0.32
	4 h	1874.57	–	0.55
	8 h	1796.25	–	1.01

TABLE XIX: Transactive operation using stochastic MPC with next-hour calibration

Approach	**Prediction**	**Objective**	**Max Iters**	**Max Time (s)**
(A) Cen-Sto-Ntran	1 h	2183.64	–	0.45
	4 h	2126.46	–	2.70
	8 h	2113.05	–	9.06
(B) Dis-Sto-Tran	1 h	(W) 1955.94	10	7.39
		(B) 1954.26	10	7.89
	4 h	(W) 1917.87	14	15.80
		(B) 1904.62	15	12.74
	8 h	(W) 1922.59	19	57.67
		(B) 1902.03	19	56.79
(C) Cen-Sto-Tran	1 h	1954.73	–	0.40
	4 h	1900.36	–	4.56
	8 h	1861.04	–	19.01

If electricity transaction is not allowed among building agents, the objective values of approach Cen-Sto-Ntran are very close for different accuracy settings of prediction with same length 1 hour, 4 hours and 8 hours. Take 8 hours as an instance, the cost objective drops only about 20 from 2133.94 (Table XX) to 2113.05 (Table XIX) when information becomes accurate after calibration in very near feature, and stays at 2102.54 even with perfect prediction with max improvement 31. On the other hand, the maximum improvement could be 124 from 1920.08 (Table XX) to 1796.25 (Table XVIII) when transaction is allowed. Thus accurate prediction is more valuable when energy could be transacted locally, similarly for prediction length. With prediction calibration for next time step, about 7200 variables could be eliminated from stochastic model and the computational cost of centralized stochastic MPC decreases from 2161 seconds (Table XX) to only 19 seconds (Table XIX). However, when one more building join in, about 19200 variables will be added, the time cost of centralized optimization frame-

TABLE XX: Transactive operation using stochastic MPC with stochastic prediction

Approach	**Pred-iction**	**Objective**	**Max Iters**	**Max Time (s)**
(A) Cen-Sto-Ntran	1 h	2190.33	–	0.37
	4 h	2133.28	–	34.79
	8 h	2133.94	–	932.30
(B) Dis-Sto-Tran	1 h	(W) 2045.36	10	12.54
		(B) 2039.72	10	12.31
	4 h	(W) 1976.17	13	104.12
		(B) 1959.52	14	99.89
	8 h	(W) 1974.05	15	939.40
		(B) 1948.86	14	755.42
(C) Cen-Sto-Tran	1 h	2032.43	–	0.52
	4 h	1939.06	–	98.54
	8 h	1920.08	–	2161.62

work will change dramatically in contrast with the proposed distributed optimization approach. Overall, without knowledge of centralized information, our proposed distributed approach has competitive performance from aspects of solution quality and computation time.

4.5 Concluding Remarks

To enable efficient transactive operation and protect sensitive information, a bi-level distributed stochastic model predictive control framework is proposed for networked micro-grids and swarm intelligence is employed at system level to balance energy transactive decisions. To allocate energy resources more efficiently, marginal price of transactive energy in each micro-grid is returned to system level to guide velocity and position updating for the particles. The performance of the proposed distributed approach is evaluated and compared in day-ahead and real-time transactive operations. Experimental results show that it's validated using marginal information to guide swarm intelligence in coordinating cooperative agents and prediction accuracy could greatly improve performances in real-time decision making.

CHAPTER 5

CONCLUSIONS

In this thesis, the emerging local energy transaction of prosumer (building) at distribution level is focused. Decision models and efficient algorithms are developed to study the collaborative energy transaction decisions of building clusters in three research phases.

Number of research has demonstrated that building clusters can achieve more benefits like lower total energy cost, however, some buildings have to make sacrifices of their own interests for collective interests for the clusters. To motivate individual buildings, we propose four different transactive energy management models in first phase where each building is allowed to have energy transaction with others while individual requirement has to be satisfied. The first model focuses on maximizing collective interests and this model is appropriate when all the buildings are operated by one manager, both collective and individual interests are considered in second model which is suitable when different buildings have heterogeneous individual interests. The third and fourth models aim to maximize both collective and individual interests, this two models are preferred when buildings have homogeneous individual interests (e.g. same saving percentage or absolute saving amount).

Then next, in second phase, large scale (e.g. community level) building clusters is studied. To enable more efficient transactive operations among prosumers, we propose a swarm intelligence based bi-level distributed decision approach. Particle swarm optimizer is employed at system level to coordinate all the buildings to dispatch shared energy while each building at sub-system level will employ a mixed integer operating model to obtain operation decisions for its energy systems, such as distributed generators and storage systems. For the purpose of accelerating convergence of swarm algorithm, a marginal price based feedback strategy is proposed. During each iteration, each building will solve its local decision model, the marginal prices for exchanged energy will be collected and fed back to system level to guide velocity and position updating of particle swarm. Proposed distributed approach is applied on distributed control for building-charging station integration as a case study, and then it is evaluated in terms of accuracy, scalability and robustness. It is demonstrated that proposed approach is very computationally efficient, scalable and robust, and the computational complexity if $O(n)$ where n is the number of buildings in the cluster.

To deal with uncertain information about electricity load and solar radiation, scenario-based centralized two-stage stochastic operation model is firstly established at third research phase, where electric storage and power generating unit are assumed to provide different kinds of operating reserves in ancillary market. Proposed swarm intelligence based distributed decision framework and coordination algorithm from previous phase are extended to incorporate with stochastic programming. In order to further decrease model complexity of planning optimization and utilize updated information, model prediction control approach is embedded in proposed energy transaction process to make online decisions.

In summary, this thesis has proposed a swarm intelligence based methodology of coordinating buildings' transactive operation at distribution level. The main idea is to utilize marginal information from individual optimization to allocate resources more effectively for collective optimality. This methodology could be adopted for more applications, such as robots swarm coordination, etc. There are, however, several issues that could be addressed in future investigations. For example, only electricity transaction is allowed in research phase II and III, multiple transacted energy resources (heating, cooling and electricity) will be considered, and the correlation between different kinds of energy resources will be emphasized. In addition, the energy transaction price of local transaction market is assumed based on transparent information in research phase I. Pricing negotiation mechanism will be worth developed based on game theory to optimally determine local energy transaction price. More broadly, from system perspective, uncertainty coupling and propagation from different sources may have great impacts on the algorithm performance, also communication between system level and subsystem agents may be delayed and missing, therefore distributed coordination algorithm should be robust when facing with such unexpected conditions in practice.

APPENDIX

Chapter 2 was firstly published in *Energy*, and is cited as (15) in References. Section 3.4.1 in *Chapter 3* was firstly published in *ASME proceeding 2017*, and is cited as (16) in References. The permission to include these two previous publications are attached here.

Figure 19: Permission 1

APPENDIX (Continued)

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VITA

Yang Chen

EDUCATION:
B.S., Industrial Engineering, Henan Polytechnic University, China, 2006-2010
M.S., Industrial Engineering, Chongqing University, China, 2010-2013
PhD, Industrial Engineering, University of Illinois at Chicago, U.S., 2013-2017

PROFESSIONAL MEMBERSHIPS:
American Society of Mechanical Engineers (ASME)
Institute of Industrial and Systems Engineers (IISE)
Institute for Operations Research and the Management Science (INFORMS)

JOURNAL PUBLICATIONS:
Chen Y, Hu M., Zhou Z. (2017): A Data-Driven Analytical Approach to Enable Optimal Emerging Technologies Integration in the Co-Optimized Electricity and Ancillary Service Markets. Energy, 122, 613-626

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Chen Y, Hu M. (2017): Swarm Intelligence based Distributed Stochastic Model Predictive Control for Transactive Operation of Networked Micro-grid Clusters. IEEE Transactions on Smart Grid, (Under Review)

CONFERENCE PROCEEDINGS:

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Chen Y, Hu M. (2017): A Guided Particle Swarm Optimizer for Distributed Operation of Electric Vehicle to Building Integration, Proceedings of the ASME 2017 International Design Engineering Technical Conferences & Computers and Information in Engineering Conference.

Hu M., Chen Y, Li X., Xiong K.(2017): An Agent-Based Simulation Model for Distributed Vehicle Sharing Operations, Proceedings of the 2017 INFORMS Winter Simulation Conference.

RESEARCH INTERESTS:

Smart Building-Smart Grid Operation, Complex System Optimization, Engineering System Design, Data-Driven Optimization, Distributed Agent Coordination Algorithm