

MARKET-BASED POWER MANAGEMENT AND CONTROL OF RESILIENT
SMART GRIDS AND MICROGRIDS USING A GAME THEORETIC
MULTI-AGENT SYSTEM APPROACH

by

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ABSTRACT

In this dissertation, we address the problem of optimal resource allocation through distributed market-based techniques in future power systems. Several connected problems are considered in different stages of this research project: 1) optimal decision making of generation companies in wholesale markets, 2) demand response and energy pricing in retail markets, 3) single and multiple microgrid power management within the retail sector, and 4) introducing a resiliency-aware power management for microgrid-based distribution systems. Hence, this work addresses the challenges that are connected to the economics of energy.

All of these problems are concerned with optimizing the behavior of the participants in electricity markets (in wholesale and retail sectors) to achieve certain objectives in power system operation (e.g., profit maximization, peak shaving, resiliency improvement, extreme event awareness and preparedness, etc.). Solution concepts from the fields of machine learning and game theory have been employed to address these problems. Moreover, distributed agent-based frameworks are designed for modeling the interactive decision making processes and implementing control laws in electricity markets. The goal is to introduce automated “intelligent” decision making capabilities into power systems to improve the efficiency of grid operation. This is closely related to the concept of “smart grids”.

The proposed solution strategies are verified through numerical simulations in MATLAB environment. The results demonstrate that using the proposed distributed decision tools and machine-learning-based techniques we can improve the performance of power systems to achieve higher levels of controllability and efficiency, while enhancing system resiliency.

INTRODUCTION

Background and Challenges

Electrical energy infrastructures around the globe have been undergoing a restructuring process in the past few decades [49]. The purpose of this restructuring process is to introduce the concept of market-based competitive resource management into the electrical power industry, which is believed to result in more efficient ways of handling problems and challenges. Based on this modern outlook, electrical energy and other related ancillary products (such as reserve power and regulation power) are treated as tradeable goods sold or bought on electricity markets at different levels (wholesale/retail) and time scales (day-ahead/hour-ahead/real-time) [156]. Hence, electrical energy markets have been developed to provide an economically viable and efficient framework for trading the products that are essential in maintaining the functionality of power systems. The basic requirement for an energy market is for the buyers and sellers to have open access to the power transfer conduit, namely, the transmission system. Open access to transmission lines was established through order No. 888 by Federal Energy Regulatory Commission (FERC) in the US in 1996 [66]. This led to the introduction of the concept of non-profit Independent System Operator (ISO) and Regional Transmission Organizations (RTO) for managing the transmission systems, in order to encourage competition at generation and consumption levels [187]. Different wholesale market entities providing service in different regions of US and Canada are shown in Fig. 1.1 [65].

While the introduction of market mechanism in electrical energy networks has created a dynamic environment for competition and efficient resource allocation in the

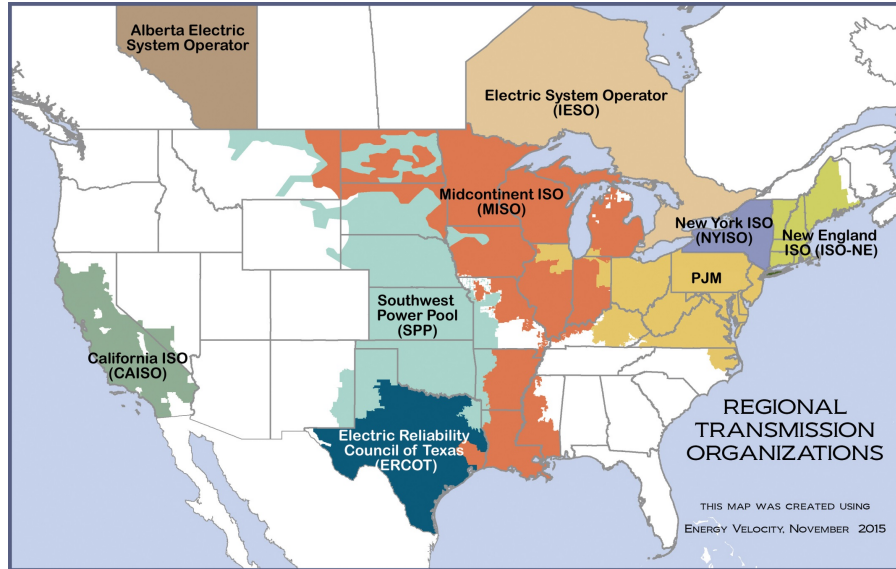


Figure 1.1: Wholesale markets across northern America [65]

industry, it has been shown that poorly designed market-based energy management systems can lead to catastrophic outcomes. One example is the California electricity market collapse in 2000, due to power withdrawal of Generation Companies (GenCos) supplying the region, during peak load periods [192]. This crisis led to extensive modifications in the California market, and signified the importance of good market design and decision tools. Basically, proper market design mechanisms for different energy networks is a critical task that requires intense planning.

This dissertation is mainly motivated by several challenges in the field of market theory employment in the electrical power industry. These challenges which span both wholesale and retail sections are introduced below. The main objective of this project is to provide solutions to the problems that are related to the economics of energy and are caused by the evolving structure of power systems. In other words, in this work we will propose market-based resource allocation techniques to ensure the

improved efficiency of system operation, while maintaining critical constraints. The specific proposed solutions to each of these challenges will be discussed in the next sections.

Decentralization and Smart Grid

Introducing market mechanisms in power systems implies higher levels of autonomy and independence for different parties, such as GenCo owners, in the industry. Consequently, this leads to decentralization of the decision making structures in the energy networks [117]. In other words, participating parties in wholesale markets should be able to make decisions individually to fulfill their private goals.

On the other hand, at the distribution level, the advent of distributed generation systems (i.e., small scale power generation units installed close to consumption sites) has sped up the process of decentralization. These distributed generation systems (including renewable power sources) have been added to the distribution system with an increasing pace. It is estimated that by 2020, 33% of the total electrical power in the state of California will be provided by renewable resources. This portion will increase to 50% by 2030 [188]. Fig. 1.2 shows the growth of Photo-Voltaic (PV) power at different sectors in US in the past years [74]. Also, Fig. 1.3 shows the annually added and cumulative capacity of wind power in the US in the past decades, which demonstrates an increasing trend [52].

Along with distributed generation resources, the use of Energy Storage Systems (ESS) in the power grid is also experiencing a growth. The rate of growth of ESS in different sectors throughout the US can be seen in Fig. 1.4 [73]. Given that the cost of ESS is expected to fall in the future (as shown in Fig. 1.5 [180]), we can surmise that the penetration of ESS in electricity markets (both at wholesale and retail sections)

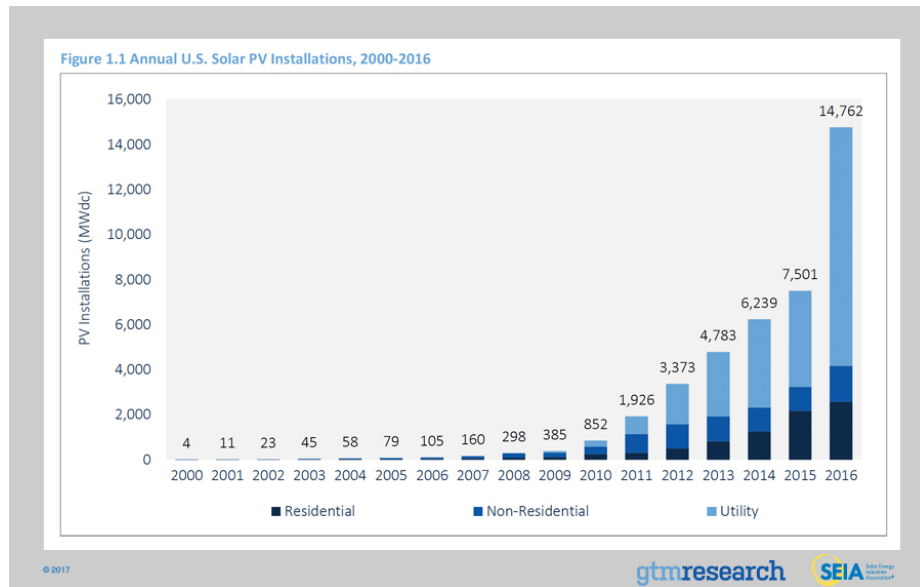


Figure 1.2: Annual PV power growth in the US [74]

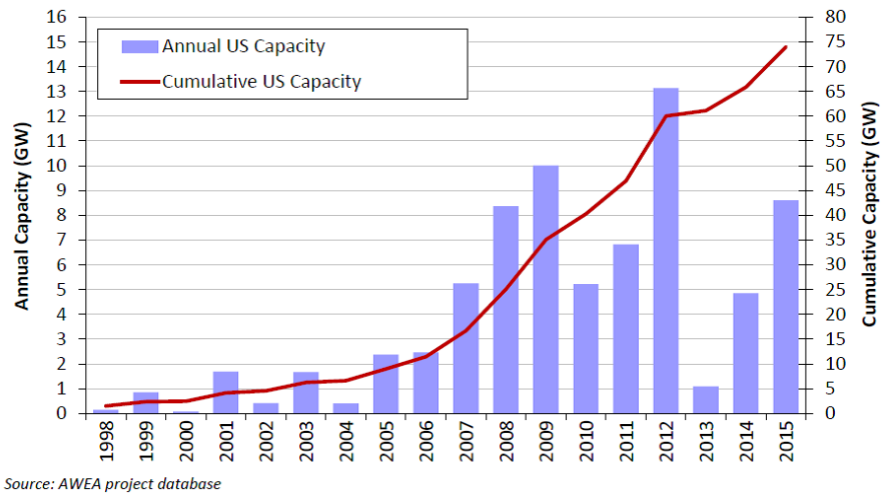


Figure 1.3: Wind power growth in US market [52]

will increase.

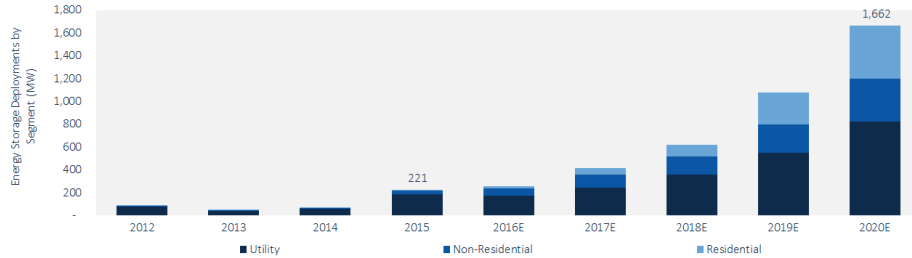


Figure 1.4: Annual ESS power growth in the US (past values and estimated future levels) [73]

As the number of distributed generators and ESS at the distribution level grows their central management and control becomes a hard and even impossible task. Basically, the amount of data required to make optimal decisions in real-time is too high for a central control unit to handle. Apart from the computational complexity of the management task, a central controller implies a single point of failure in the decision system, which means inability to address problems such as data privacy and cyber-security.

To handle the decentralization process and ensure the efficiency of operation of different resources in the energy networks, the concept of Smart Grid (SG) [221] has been introduced into the industry. A SG is basically an energy network that employs modern control and decision making techniques (such as AI and machine learning) along with a communication infrastructure for data exchange among different parties and entities. Hence, an SG represents a hierarchical and interactive decision and control architecture for energy networks to facilitate optimal resource allocation across the power system. While in conventional power systems, the flow of information is from the distribution systems towards the decision making units close to transmission level, in SG environment bi-directional flow of data between different parties at the distribution level becomes commonplace [93]. Hence, SG introduces higher levels of

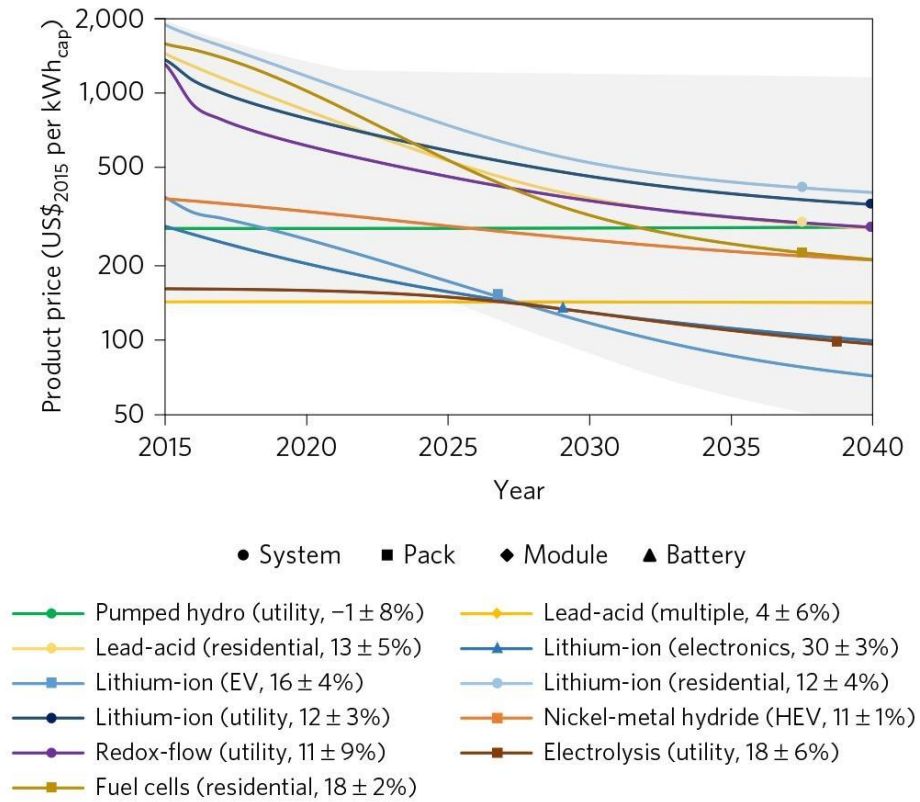


Figure 1.5: The cost of different storage technologies (past values and the estimated future levels) [180]

flexibility and controllability into the distribution systems to enable optimal resource allocation and efficient control in these systems through retail market mechanisms (i.e., active distribution system).

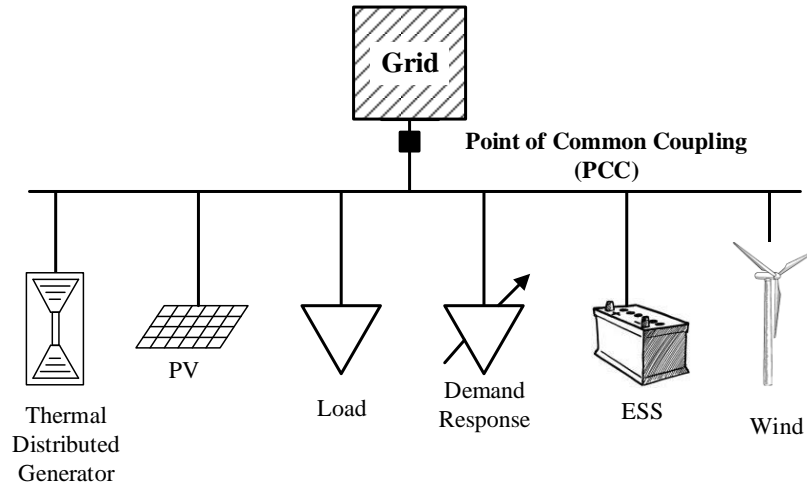


Figure 1.6: Structure of a generic MG

MicroGrids (MGs) are the building blocks of SGs [63]. An MG is a small-sized self-sustaining energy hub with its own power management capabilities. A generic MG is shown in Fig. 1.6. It can be thought of as a small cluster of distributed generation units and “smart” consumers, which can provide Demand Response (DR) services (i.e., change their consumption pattern at the behest of system operator) [168]. The availability of local generation and storage units within an MG implies that the MG has a certain degree of “self-adequacy”. In other words, an MG can operate in islanded mode if necessary (i.e., disconnected from the main grid), with minimum loss of load and disruptions to its consumers. It is expected that the electrical energy distribution system will evolve into an active network of autonomous “intelligent” data management and control centers within MGs that by sharing information achieve a secure energy supply system. Hence, the notion of SG has its roots in this vision:

a “cyber network” (i.e., a network of intelligent controllers) on top of the “physical network” (i.e., a network of distributed generation units and loads), as shown in Fig. 1.7.

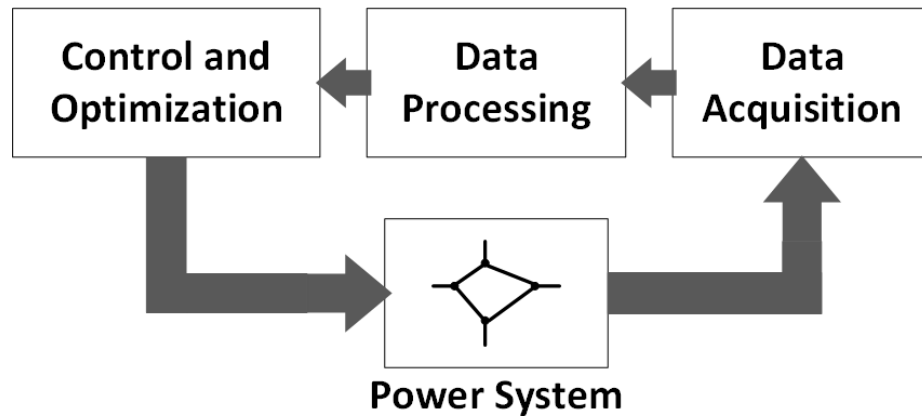


Figure 1.7: Overall functionality of a cyber-physical system

The challenge in a decentralized and hierarchical setting is to decompose decision making and control tasks among different parties in order to have a globally operational and efficient system [20]. To achieve this, distributed reasoning and optimization techniques need to be incorporated in the energy management logic of different parties in the energy network (MGs, GenCos, etc.) for them to be able to participate in local power markets. Thus, the continued decentralization of power systems should be accompanied by an in-depth study of distributed decision making techniques.

Wholesale Market Design

The purpose of the wholesale market is allocating electrical energy via bulk power plants. At the wholesale market level, GenCos compete with each other over supplying the bulk load. Essentially, GenCos are privately or publicly owned major power plants. The participation of GenCos at the wholesale level is in the form of submitting

bidding functions to the ISO/RTO, which operates the market based on the received bids and predicted value of load [51]. The goal of the privately owned GenCos is to maximize their profit from sales of energy in the market. However, the challenge here is that this decision making takes place under uncertainty. The uncertainty in the market is majorly caused by the strategic behavior of competing GenCos, stochastic behavior of load, and the possibility of generation unit failure. Renewable energy sources, such as wind and solar power, with their intermittent power output are another contributing factor to the uncertainty, especially for wind farm and solar farm owners. Noting the ambitious plans to expand the use of renewable power in electrical power industry, it is essential to develop tools that are able to model how stochasticity and uncertainty affects the market equilibrium.

Wholesale market is an example of interactive decision problem, since the action of each autonomous GenCo affects the utility value of its competitors. Therefore, each GenCo is a source of uncertainty for its competitors. In other words, when a GenCo is solving its private profit maximization problem to develop a strategy for participation in the wholesale power market, it is facing a non-deterministic decision problem, which is not easy to solve [69].

Another notable fact on wholesale markets is their hierarchical and decentralized structure: at one level, each GenCo solves a profit maximization problem to optimize its behavior in the market. At another level, the ISO/RTO solves a social welfare maximization problem based on the received participation data from the GenCos. Note that the ISO/RTO does not have direct access to the real underlying cost data of the GenCos, which is a private sensitive characteristic of the players. Hence, GenCos interact directly with the ISO/RTO through submitting bidding functions, and indirectly with each other, through affecting market equilibrium [103].

As a conclusion, when addressing the problem of optimal decision making in

the wholesale market for the purpose of designing a decision tool for the GenCos or developing a monitoring tool for the market designer, the solution approach should consider the autonomy of GenCos, the hierarchy of decision making, and the uncertainty of the market environment.

Retail Market Design

At the retail market level, a retailer agent (a utility company) buys the electrical energy from the wholesale market and sells it to the end-user consumers [209]. The goal of the investor-owned retailer is to maximize its utility value (i.e., profit level) from the sales of energy by obtaining the optimal retail prices. In the US, the retail markets are generally regulated by the state-level commissions [51]. Currently, most of the retail and distribution-level markets are operating under fixed prices (i.e., end-users pay fixed electricity rates for the power they consume) or Time-of-Use (ToU) pricing, at best [43]. The fixed retail price reflects the long term average price of the wholesale market [2]. While this fixed-pricing policy shields end-users from the risks represented by the wholesale markets, it is believed to be the cause of a considerable portion of market anomalies and failures [190]. Basically, fixed pricing at the retail level implies that in the short term consumers are not exposed to the dynamics of the wholesale markets; hence, at the wholesale level, GenCos face a stiff and price-insensitive bulk load. The stiffness of the retail market can cause abnormal wholesale price surges as high as 300 times the prices that consumers pay at peak load periods, which can cause instability and market failure [210]. To tackle this problem, the concept of DR is devised in the context of SG. The idea behind DR is to allow the consumers to participate and contribute to the control and decision making process of energy networks, using automated Home Energy Management (HEM) systems at residential and commercial levels [80]. Hence, the goal of DR programs is to make the

demand side sensitive to the dynamics of power systems and consequently increase the overall flexibility and efficiency of the system.

DR is defined by FERC as “changes in electric usage by end-use customers from their normal consumption patterns in response to changes in the price of electricity over time, or to incentive payments designed to induce lower electricity use at times of high wholesale market prices or when system reliability is jeopardized” [67]. DR programs are classified into two groups: 1) incentive-based DR programs, in which the system operator provides consumers with monetary incentives in return for various services, such as frequency and voltage regulation services, direct load control, and emergency DR. On the other hand, 2) time-based DR programs, are price-based procedures, including time-of-use pricing, peak-pricing, and real-time pricing.

The basic idea in price-based DR is to introduce short-term variable pricing through market mechanisms at retail level, to which automated smart load controllers are able to respond. In this way, a level of “price-sensitivity” can be achieved on demand side, that is, consumers change their consumption patterns in response to varying prices they receive. Thus, through price-based DR the consumers would transform from being “price-taking” parties to “price-making” entities. As shown in [102], in order to maintain the economic efficiency and viability of the markets in practice, the response of the consumers to retail energy prices needs to be considered and integrated within the pricing process of the retail market. This implies the need for developing smart metering and bidirectional communication networks between consumers and distribution utility companies that act as retail market operators. The nationwide penetration of advanced metering devices throughout US increased to 36.3% of all the metering devices by July 2014, which shows a promising trend in implementation of DR programs [68].

FERC has determined that DR providers should be compensated in wholesale

energy markets at the market clearing price, through order no. 745 (upheld by the US Supreme Court) [64]. While this order is aimed at introducing DR at the wholesale level (under FERC’s regulatory authority), it has been speculated that the disconnection between retail and wholesale pricing mechanisms could be a barrier against efficient and higher participation of consumers in the DR programs [64]. Lack of dynamic retail pricing, and real-time information sharing are named as the factors that contribute to this disconnection. The estimated rate of growth of DR market size in US power grid is shown in Fig. 1.8 [72]. As can be seen in this figure, FERC order no. 745 is expected to lead to even growth in the DR market.

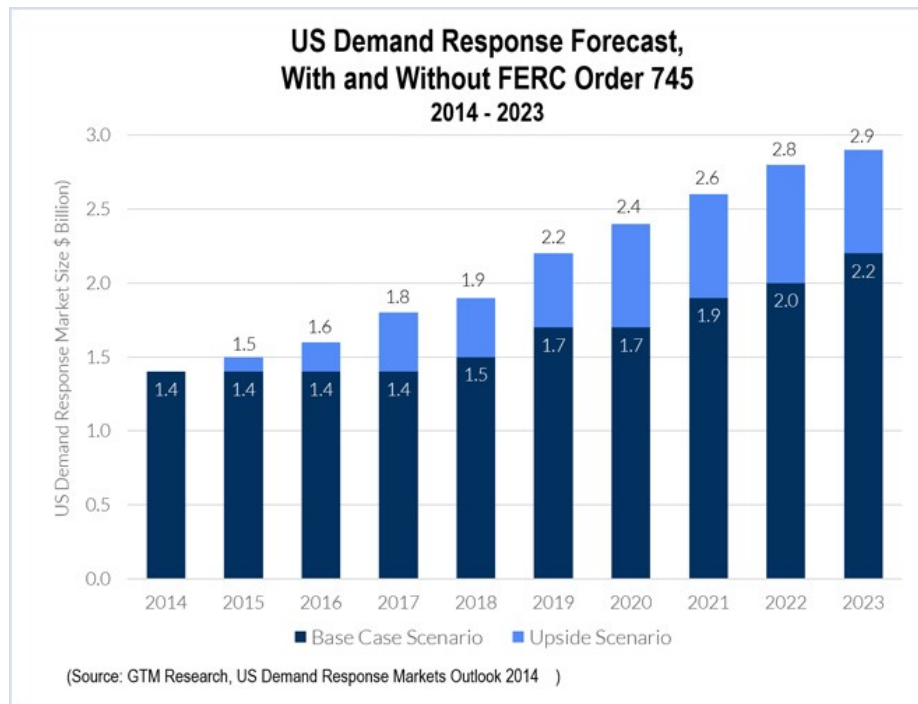


Figure 1.8: Estimated growth of DR market size in US [72]

Designing a functioning retail market mechanism requires considering several critical issues: Firstly, the decision problem at consumer control level needs to be solved autonomously, considering cost of consumption and the consumers’ private

preferences. Secondly, the retailer should develop a strategy for optimizing the retail price considering the response of the consumers. Note, that the retailer does not have direct access to the private user settings and data on the consumer-side. Hence, a hierarchical structure, involving decision making under uncertain conditions, can be observed in the structure of the problem.

Thus, a solution strategy for retail market design should include the aggregate DR from end-users in the pricing mechanism. Also, the problem of low-level decision making for the participation of consumers in the retail market should be solved taking into account different competing objectives that the end-users have (e.g., cost versus comfort).

Power Management for MGs

In an MG with various resources, such as local distributed generation units (including renewable-based sources) and controllable loads, it is essential to design an efficient resource allocation process that performs power management within the MG and coordinates its behavior with the upper-hand grid. Note that the problem of energy management in MGs is dominantly a cooperative multiobjective optimization problem [42]. Hence, each resource within an MG has several operational objectives, such as cost, efficiency, comfort level, etc. An MG-based market design mechanism for a single MG should lead to a set of trade-off solutions for these objectives, which reflects the cooperative nature of the resource allocation process. The set of non-dominated trade-off solutions in a multiobjective setting is known as the “Pareto-frontier” [44]. Any deviation from this set results in a loss for at least one of the parties. Since we usually have a multitude of candidate solutions, a single trade-off solution should be chosen from the Pareto-frontier set of the objective space of elements. The challenge is how to find a justifiable single solution on the Pareto-

frontier efficiently to maintain a reasonable balance among different objectives.

Another issue related to the energy management of MGs is that how multiple MGs on a distribution feeder contribute to the resiliency of the system. Resiliency is defined in [197] as: “the ability to prepare for and adapt to changing conditions and to withstand and recover rapidly from disruptions.” The causes of disruption include extreme weather-related events (e.g., hurricanes, and storms), earthquakes, cyber and physical attacks, and major electric faults. A few major power disruptions are shown in Table 1.1.

Table 1.1: Major Recent Power Disruptions

Country	Date	Reference
Australia	2016	[213]
China	2008	[85]
India	2012	[173]
UK	2003	[15]
Ukraine	2015	[57]
US	2003	[137]

The concept of resiliency, has been defined as part of the “self-healing” function of smart distribution systems. Self-healing refers to a wide variety of techniques that contribute to the highly reliable and uninterrupted flow of power in the SG environment [118] [203]. A self-healing power grid is able to automatically predict, detect and isolate faults and faulty elements within the grid with the least disruptive effects in system operation and power flow. As pointed out in [203], self-healing and

resiliency can be achieved through a decentralized MG-based system architecture. Hence, one of the core goals of SG technologies is to improve system resiliency and self-healing capabilities through cooperative MGs at the distribution level. The different stages of resilient operation of a power system are shown in Fig. 1.9 [196].

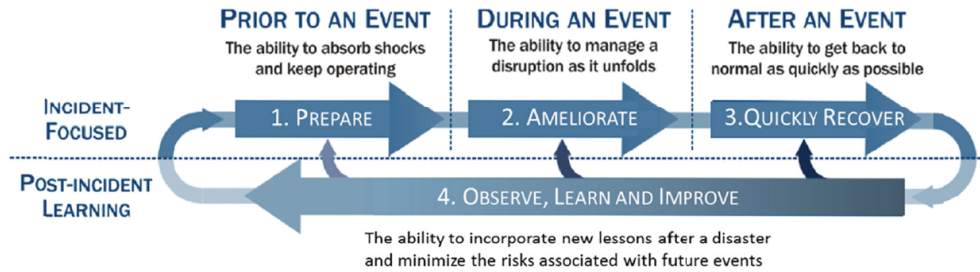


Figure 1.9: Different stages of operation of a resilient power system [196]

In a conventional power system, major faults and catastrophic natural events lead to cascading failure of the main grid or upper-hand feeders, which in turn results in wide-ranging black-outs and expensive disruptions. However, if high number of self-adequate MGs with islanding capability are employed at the distribution feeders, it is possible for them to supply the local consumers with energy, in case the main grid is offline due to hazards. Hence, a market-based mechanism at the retail level is required to allow fair power exchange and trading among different neighboring MGs when the energy supply from the national grid is disrupted [204]. Through this local trading mechanism, the MGs are able to cooperatively eliminate the regional power deficit or excess, in order to keep the system operational.

A notable issue is the hierarchical and decentralized structure of the problems related to power management of MGs. At the lower level, within each single MG, different resources with different objective functions need to cooperate with each other to reach a solution for MG power allocation. At the upper level, the neighboring MGs

negotiate with each other for power exchange and for enforcing global (network-wide) constraints. At the highest level, the retailer agent (e.g., utility company) interacts with the MGs to perform energy pricing based on the price-sensitivity of the MGs.

To conclude, a solution strategy for the purpose of market-based resource allocation in MGs should address the cooperative and multiobjective nature of decision making within each MG. Also, noting that different resources in different MGs could potentially have different owners, a distributed solution strategy should be employed to implement the interaction procedure between different parties.

Agent-Based Design

In the past decade researchers have focused on answering the above challenges, shedding light on the future of the energy industry. The focus of this research is on developing new techniques and tools that can be used to solve critical problems related to the economics of electrical energy. The details of these problems will be introduced in the next section. We expect that these techniques will be incorporated into power systems brought online in the near future. The general framework of the proposed solutions in this research is based on Multi-Agent System (MAS) theory.

Using an agent-based approach [211] adapted from the fields of AI, machine learning, and game theory we will be able to model the behavior of energy networks with a decentralized and hierarchical structure in SG environment. Agent-based designs are used for distributed control and decision making tasks among several intelligent controllers or “agents”. Hence, an agent-based vision in approaching the market design problem seems to be logical. By installing a high number of intelligent controllers that are capable of communicating with each other throughout the power system, the conventional electrical energy system will transform or move closer to the SG environment. Ultimately we would like to re-design the operation of power

systems from an agent-based perspective.

According to [216], an agent can be defined as an artificial computer system or in a more general sense, an entity within an environment that has the following vital properties:

- **Autonomy:** agents are autonomous, by which we mean they are capable of pursuing their objectives through individual and “self-interested” decision making. Here, the phrase “self-interested” implies having private/independent computational capabilities (and even goals).
- **Interaction:** Agents are able to interact with their environment and with other agents. This interaction occurs either by sending/receiving data from sensors or through a communication network, while maintaining some level of privacy and confidentiality. Hence, agents are “social” entities that can achieve their private/social goals through interactions with each other and reacting to their environment.

As described above the concept of “agent” can be applied to a wide range of academic disciplines. As described in [185], “MASs are systems that include multiple autonomous entities with either diverging information or diverging interests, or both.” This dissertation is interested in using agents within a control theory context. Hence, from our perspective, agents can be thought of as independent controllers in charge of managing their private assets (e.g., controllable loads, distributed generators, MGs, GenCos) independently in the electrical energy market. These controllers are distributed throughout the power system at different levels of market hierarchy and are able to send/receive signals to/from their peers, which fits well in the context of the decentralized structure of power systems. Our goal is to design intelligent agents

that are able to provide collective solutions to the complex problem of modeling electrical energy markets and energy management systems.

One critical aspect of agent-based modeling in energy markets is that, as discussed before, different parties and their controlling agents do not have access to all the information needed to directly solve a problem. While agents receive data through local measurements and interaction with their peers, the uncertainty cannot be eliminated altogether. One significant factor contributing to this problem is data ownership. This is a vital issue as the electrical energy network evolves with time. In this context, the agents, especially on the electrical demand side and investor-owned GenCos, refrain from sharing critical information with others. Hence, reasoning under uncertain conditions and incomplete information needs to be addressed.

Another aspect of agent-based modeling addressed in this dissertation is the ability of the agents to obtain their optimal courses of action by “generalization,” where good solutions are found to new situations, based on past exposure to the environment. Generalization is achieved by using techniques from machine learning for agent-based model development [185]. These used tools will be discussed in more details in the following chapters of this dissertation employing the concept of “learning agents”.

MAS theory is closely connected to two other scientific areas that are also highly relevant to this dissertation: game theory, and distributed optimization. Here, we present a very brief description of these two disciplines. The details of different tools and techniques adopted from these areas are described in next chapters of this work.

Game Theory

As described in [132], game theory was developed to describe situations of interactive decision making. In this context, a game consists of several players (i.e.,

agents) that interact with each other to satisfy their objectives. A game consists of a certain set of probabilistic or deterministic rules and procedures that map the actions of the players to certain outcomes. At different outcomes the players receive different pay-offs (which also depend on each player's evaluation of the outcome). Hence, in general, the goal of the players is to improve their pay-off levels within the game.

In the field of game theory, different solution concepts are used to describe and predict the behavior of the system. The two significant solution concepts employed in this dissertation are as follows [10]:

- **Nash Equilibrium (NE):** The NE is used in the context of non-cooperative game theory (e.g., modeling competition in a market). NE of a game represents the *stable* point of operation of the system. Intuitively, NE is achieved when all the players are implementing best response strategies to each other (i.e., no single player has any incentive to deviate from the equilibrium unilaterally). The concept of NE is discussed in more details in Chapter 2.
- **Nash Bargaining Solution (NBS):** NBS was proposed as a solution concept to address situations of cooperative bargaining among multiple parties. A bargaining game consists of a set of players with different pay-off functions trying to reach a Pareto-optimal solution through negotiations. NBS is a unique solution to the bargaining games, that is located on the Pareto-front and introduces a fair balance between the pay-off functions of different players. A more detailed mathematical description of NBS is presented in Chapters 5 and 6.

The two solution concepts introduced above are used in the next chapters of this dissertation to design agent-based power management and control mechanisms for the power markets, at the wholesale and retail levels.

Distributed Optimization

Distributed optimization techniques are another class of methodologies that are closely connected to agent-based modeling. Within the context of distributed optimization, a group of control agents interact with each other through a communication system. Basically, a global optimization problem is decomposed into multiple simpler tasks which are allocated among the agents. Each agent is in charge of solving its own sub-task and sharing the solution (or portions of the solution) with its neighbors. After receiving the solutions of its neighbors, the agent then updates its own solution, accordingly. The objective of a distributed optimization framework is to ensure that the private solutions of all the agents converge to the same value. That value is the solution of the global optimization problem.

Various distributed optimization methods have been proposed in the literature. Distributed synchronous and asynchronous subgradient-based methods [148–150], Lagrangian-decomposition-based algorithms [92, 229, 237], distributed Newton-type approach [207], diffusion strategies [36], and dual averaging [54] are a few of noteworthy works done in this area. A review of different distributed optimization techniques from a control engineering perspective has been presented in [147].

In this dissertation, we have employed agent-based distributed optimization techniques in Chapters 5, 6, and 7 to solve the power management problem of the single and multiple MGs using the concept of NBS. More details will be discussed in each Chapter.

Market-Based Control

Market-based control, also known as “transactive control” and “transactive energy” is defined by the GridWise Architecture Council (GWAC), [78] 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.” Hence, basically, the goal of market-based control is to enable power trading and transactions between different parties at different levels of the hierarchy of the electrical energy industry. The key concept in the definition of transactive-control is the notion of “value”, which can be interpreted as “price” or “cost” in the context of traditional market; however, this concept can have other interpretations based on the context it is being used. It can be concluded that the main objective of transactive control is to introduce well-known market-based mechanisms at different levels of decision making in power systems, specifically at the electrical distribution level through retail markets (it has been argued that the wholesale market already falls into the transactive control systems category [170].)

The relationship between market-based control and SG becomes more clear as the two basic properties of transactive control are taken into account, as shown in Fig. 1.10 [106]: 1) existence of a two-way communication network, and 2) local decision making. Hence, the agents that participate in a market-based control setting not only “react” locally to the price/value signals they receive, but also seek to affect the behavior of their peers through sending value/price signals of their own, which in turn makes them “active” agents. The vision of market-based control is to transform the traditional power systems into an interconnected network of autonomous agents that are able to overcome disturbances (e.g., the intermittency of renewable power, cascading failures and major faults in a portion of the system, and environmental disasters) through cooperative power sharing and local decision making.

Several small transactive energy projects have been implemented throughout the US: Olympic Peninsula demonstration (2006-2007) [79], AEP Ohio gridSMART real-time pricing demonstration (2010-2014) [1], and Pacific Northwest Smart Grid

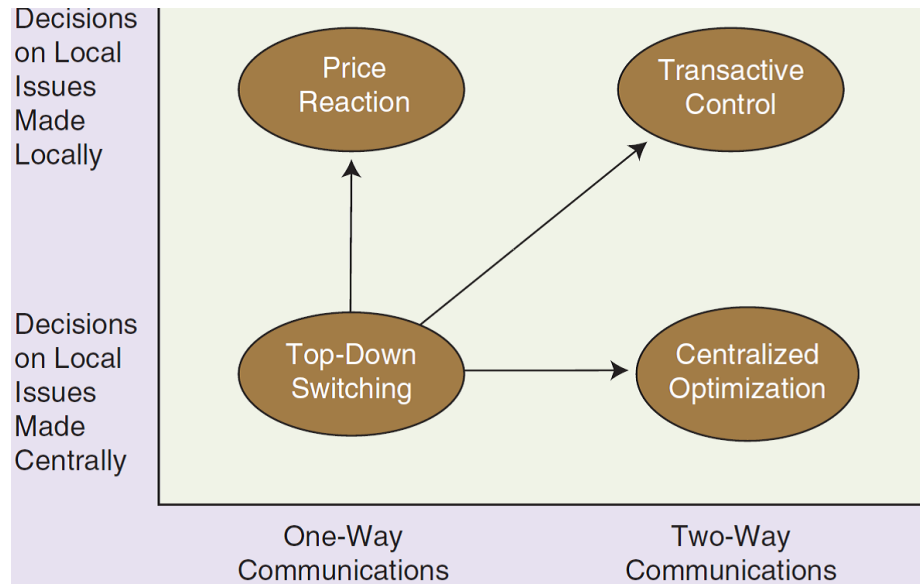


Figure 1.10: The properties of different control logics [106]

demonstration (2010-2015) [166]. These projects demonstrate the interest in the industry on employing the new concept of market-based (transactive) control for handling energy management and operation of power systems. Also, promising results, in terms of reducing cost and peak load were observed.

This dissertation, as mentioned earlier, is aimed at studying the economics of energy under new paradigms, one of them being SG and market-based control. The proposed solutions to different problems employ data exchange among market-aware agents along with local decision making mechanisms to design pricing and dispatching models for efficient resource allocation and energy trading among different parties, under normal and abnormal conditions (after extreme structural changes in the system). Hence, the framework drawn in this research can be categorized as market-based (transactive) control.

Literature Survey

In this section a literature review of different topics of interest is presented. Also, each chapter of this dissertation has its own survey of critical and relevant articles.

A surge has been observed in the use of MAS theory in the field of electrical power engineering in recent years, which shows a consensus in the community on the advantages and strengths of agent-based modeling approaches in solving complex engineering problems. Also, the introduction of modern communication techniques and infrastructure in electrical energy industry has created a favorable context for implementation of agent-based logics. A general review on the concepts, tools, and challenges of MAS theory for power engineering problems can be found in [134], and [135]. A wide range of applications have been studied in this setting, and agent-based solutions have been proposed for them: system restoration [144, 151, 172, 189], monitoring applications and anomaly detection [128, 175], voltage control [8, 62, 89], generation and transmission planning and expansion [141], islanding detection [90, 91] and network reconfiguration [50] are among them. The body of literature that are related to the objectives of this proposal (i.e., electricity markets, market-based control, and MG power management, and system resiliency) are briefly reviewed in the following subsections.

Wholesale Market

MAS theory has been previously used to model wholesale electrical energy markets [210]. Most of the work done in this area is based on Reinforcement Learning (RL). In [192], the 1999-2000 California energy crisis is studied using an intelligent MAS platform to identify the causes of market failure. A MAS-based gradient descent continuous actor-critic algorithm is proposed in [236] to model the learning process

of different parties participating in day-ahead electricity markets. In [25] a naive rule-based RL scheme was proposed to model strategic bidding in electrical energy markets. In [145] and [146] another RL-based decision making process was proposed to model the effect of water shortage on electrical power generation. The effect of initial beliefs of the agents employing RL on the market was examined in [14]. Among different RL-based algorithms, Q-learning has primarily been employed towards agent-based modeling of wholesale electrical energy markets. In [194], Q-learning was used to model capacity withholding and tacit collusion. Q-learning has also been used in [227] to develop an agent-based model for studying the effects of different market rules.

While RL is a powerful tool that provides invaluable insight into the operation of wholesale energy markets, its use has been limited to the case of discrete agent action spaces, which may result in sub-optimal solutions to the problem. Other possible agent-based decision making models have mostly been ignored. Dynamic Programming (DP) is one such alternative model, and has been used to solve the decision making problem of agents in a wholesale market. While DP is closely related to RL, it requires the full knowledge of the whole decision model by the agents, and is also based on discretizing the action space. In [183], a multilayer agent-based decision model for energy markets was presented based on stochastic programming and scenario generation. Stochastic programming in combination with a branch-and-bound method was also used to implement a MAS-based model of electrical energy markets [182]. The main difficulty with stochastic programming is the need to estimate probability density functions a priori, which are possibly non-stationary. Also, a MAS-based constrained gradient algorithm is proposed in [232] for optimal thermal generator power management in power systems. An agent-based distributed dynamic programming algorithm is proposed and implemented in [219] to provide

solution for online economic dispatching problem.

Other (non-agent-based) modeling approaches for wholesale electricity market modeling have also been published: non-probabilistic information gap decision theory [133], minimax regret model [61], and information-fusion-based control [220] are a few of these.

Demand Response

The combined use of agent-based modeling and machine learning techniques at the distribution-level energy markets with price-sensitive consumers is not well-established. However, remarkable papers have been published in this field which provide insight into the operation of retail energy markets, DR, and transactive control.

Different objectives have been defined for the utility companies and the retailers in the literature, including profit maximization [27], peak reduction [177], and total cost minimization [33]. To account for the uncertain behavior of consumers in response to retail energy prices, iterative pricing mechanisms are proposed in the literature.

In [140], the retail market is formulated as a bi-level decision problem, introducing a two-stage pricing mechanism, through a distributed convex optimization problem. While the authors have proposed a framework that protects the data privacy of the consumers, limiting assumptions have been made to keep the optimization problems convex. In [176], the reaction of demand side to energy prices is modeled as simple elasticity coefficients that appear as constraints in the optimization problem of a profit-oriented utility company. While this generic approach provides valuable insight into the decision making of a utility company, it fails to capture the dynamic behavior of demand side in the retail pricing process. In [136], purchase bidding

strategies of an energy coalition with a non-profit aggregator and DR is studied, again, through a bi-level decision problem. The authors have relied on Monte-Carlo simulations and stochastic optimization to account for the price-sensitivity of the loads in decision making. Since no learning mechanism is adopted to direct the search process, the number of iterations required to solve the problem is very high (1000). Another iterative pricing mechanism is introduced in [177] to flatten the load profile. In this paper, also, the utility company relies on estimated gradient of price sensitive demand along the retail prices. Hence, to guarantee global optimality the authors have kept the optimization problem convex. The behavior of demand under different pricing policies has been studied in [58] using a game-theoretic framework. Also, retail markets have been modeled using the concept of Stackelberg game [27, 125, 209]. A Home Energy Management system (HEM) is proposed in [3] to minimize the total cost of consumption while satisfying comfort level of the consumers at all times, using nonlinear mixed integer programming. A distributed optimization scheme is proposed in [94] to implement a DR program with a quota system that is aimed at maximizing welfare for consumers and minimizing load fluctuations. In an interesting work, the problem of uncertainty of the response of the consumers to retail prices is discussed within a bi-level decision problem [169]. In this paper the authors use an iterative scheme and a simulated-annealing-based price control strategy to remove the uncertainty of the system. Another iterative approach is proposed in [159], where Lagrangian relaxation is used to find the equilibrium of a pool-based market with a DR program.

Considering the reviewed body of the literature, among different household appliances, Thermostatically Controlled Loads (TCLs), such as refrigerators, space heaters, and AC loads, have the highest potential for participating in retail markets. This is due to the relatively high thermal capacitance of these loads which gives

the controller agents the opportunity of modifying the consumption pattern of the loads without causing discomfort to the consumers [139]. Hence, in this thesis, as was mentioned earlier, price-sensitive AC loads will be employed as candidates for designing a DR program. Optimal AC load scheduling has been reported in [129], [127], and [34] using model predictive control. As pointed out in these works a central aspect of DR is used to ensure that the comfort level constraints of the users are satisfied. Hence, any well-designed DR program should take the private preferences of the consumers under consideration.

MG Power Management

Different agent-based distributed techniques have been applied to solve the power management problem of MGs. A basic review of different distributed control techniques (including agent-based decision models) and their various applications in MGs can be found in [225]. In [226] a multilevel agent-based decision making system is proposed for power management of a hybrid energy generation system. Different control tasks at different time scales are decomposed among the layers of agents. Another hierarchical agent-based decision model for MGs is proposed in [121] using intelligent control for very short-term power dispatching. The main focus of this paper is designing a functional ontology for message passing and interpretation among agents. An agent-based framework is also proposed in [206] for primary and secondary frequency control from micro-sources on the demand side, such as electrical vehicles and electrical water heaters. In [55] a local market mechanism is proposed for MGs to perform local resource allocation. The market model is based on distributed decision making of each element within an MG.

A paper which is of particular interest to this dissertation, employs a multiobjective approach to power management of MGs [42]. The Pareto-front of

different objective functions of the system is obtained by extensive sampling. Other multiobjective approaches can be found in the literature, as well [32, 174, 235]. Since MGs normally contain more than one generating asset, including renewable generation, controllable load and ESS (with individual and overall MG objectives that can be conflicting), multiobjective optimization methods are necessary for their efficient and cost-effective operation.

Distributed optimization techniques have also been used in the literature to solve optimization problems for MG electrical power management applications. This not only leads to lower computational burden per agent, but maintains data privacy and improves security by avoiding a single point of failure. In [233] an online energy management system is proposed in which the cost minimization problem is decomposed into simpler problems and solved using distributed gradient descent method. Consensus algorithm has also been used in solving the cost minimization problem in a distributed manner [218] [223]. Population games and population dynamics represent a class of game theoretic methods for distributed decision making [16]. In [138] tools from population game theory (e.g., replicator dynamics and opinion dynamics) are used to model active and reactive power dispatching, along with DR, considering the influence of “opinion” of agents on the outcome of the problem. The proposed method is compared with traditional centralized power management approaches to prove its efficiency. Population-game-based methods, employing MAS-based frameworks, have been used in [158] to model economic dispatching problem in MGs. A hierarchical control structure for MGs is proposed in [53] where different computational tasks are distributed among different levels of the hierarchy. Another hierarchical hybrid (i.e., using both centralized and decentralized approaches) control mechanism is proposed in [130] for power management of an MG. Contract net protocol and multifactor evaluation are employed for coordination of different agents

at different levels. Using an agent-based distributed control technique and droop-based frequency regulation, a cost minimization scheme is proposed for MGs in [113]. A probabilistic MAS-based model (with different agents representing vehicles, aggregators, and retailers) was proposed in [155] to study the charging behavior of electric vehicles and their effects on distribution systems through Monte-Carlo simulations.

Several published works have also studied the problem of power trading and load sharing among several MGs. In [230] frequency reserve provision from several MGs is studied using a reserve market mechanism. Energy management of electrical vehicles in a multiple MG environment is examined in [201] using a distributed price-based method. The problem of multiple MG formation after loss of the main feeder due to natural disasters is discussed in [35]. The goal of this paper was to enhance self-healing capability of the system through searching for the optimal network structure after major problems in the national grid. Optimal clustering of distribution feeders into several virtual MGs, considering self-healing and reliability of the system, has also been studied in [6]. Power trading among MGs has been modeled and examined using Stackelberg game [111], distributed cost minimization approach [71], multi-objective power allocation [39], and performance and user satisfaction optimization [202]. In [131], a hierarchical decision procedure is proposed for a distribution system with multiple MGs. At the lower level, the MGs solve their cost minimization problem, and at the upper level, a central coordinator is in charge of eliminating overall power excess/deficit. In [153] and [154], a bi-level power management process has been proposed for distribution systems with multiple MGs, where agents participate in local and global markets by bidding.

Power System Resiliency

A review on the definition of the concept of resiliency and comparison with other concepts (such as reliability, robustness, and security) is given in [7]. In [31], a code-based metric is proposed to quantify the resiliency of power distribution systems. Several other indices are introduced in [119] to measure the impact of extreme events on power systems, using a mesh grid approach. In [200], the resiliency of power systems is studied in the post-fault stage of system operation, through Lyapunov-function-based certificates. A post-disaster scheduling scheme is proposed in [5] for cost-effective system restoration. The economics of disaster and physical constraints are taken into account. Resiliency enhancement in power systems is closely related to MG control and power management. In [30], percolation theory is used to quantify and enable the resiliency of a distribution system with multiple MGs. Also, MGs are used as resiliency resources. In [181], MGs are employed to provide various services at different levels and stages, such as local level, community level, and black start stage. A centralized resiliency-oriented MG power management scheme is presented in [100] considering different islanding scenarios. A non-cooperative game-theoretic model is proposed in [37] to study the strategic behavior of MGs, while considering system resiliency in face of failure modes. In [70], a two-stage resiliency-oriented stochastic programming for optimal scheduling of a resilient MG is employed, to mitigate damaging impact of electricity interruptions.

In [157], defensive islanding algorithms have been proposed by taking into account the impact of severe weather on power systems. A self-healing strategy is developed in [161] for two neighboring MGs, to support each other in times of load deficiency. A self-healing agent is considered that is able to operate in both centralized and decentralized modes. In [29], a two-stage procedure for a centralized self-healing scheme for distribution systems is proposed to minimize the number of

de-energized nodes. In [228], Viterbi algorithm is used to design a system restoration plan with the goal of improving resiliency. In [112], the problem of pre-positioning truck-mounted emergency generators for resilient emergency response of the grid to natural disasters is investigated; MG-formation using these emergency generators is studied.

Dissertation Objectives

Considering the challenges discussed above, several main objectives are outlined in this dissertation. The primary goal is to design agent-based solutions for economics of energy, given the decentralized and hierarchical structure of future power systems. In this section the objectives of this work (each corresponding to a chapter of the dissertation) are discussed in general terms. The details of the proposed and implemented solutions can be found in the next chapters.

Objective I: Wholesale Market Study

Goal: Introduce a basic agent-based framework for wholesale energy market. Proper tools from the fields of game theory and machine learning have been used to achieve the above goal. Agent-based approach has been employed to study how uncertainty affects market equilibrium, and how market design should be modified in order to alleviate the adverse effects of the uncertain variables. Basically, a probabilistic decision tool should be provided that can be used by both the market participants (i.e., GenCos) and market designers.

Hypothesis: 1) Using a probabilistic decision model GenCo agents are able to predict the equilibrium of the market and maximize their profit. 2) Multistage wholesale markets (i.e., markets with both hour-ahead and day-ahead decision making stages) are more resilient and stable in face of uncertainty, compared to single-stage

markets (i.e., markets with only day-ahead decision stage).

This problem is addressed in Chapter 2.

Objective II: Retail Market and DR Study

Goal: Generalize the proposed agent-based framework of the first objective to retail markets, where smart agents from the consumer side will participate in local distribution energy markets. Hence, the objective is to design an agent-based decision model to capture the behavior of price-sensitive loads (within the context of time-based DR programs). Using this framework, we would be able to study the behavior of retail electrical energy sector under DR programs. Design a proper energy pricing mechanism for load control.

Hypothesis: 1) Using a non-linear model to capture and predict the behavior of price-sensitive loads leads to higher monetary gains for the retailer, compared to a linear model. 2) Higher levels of price-sensitivity on the demand side results in lower profit level for the retailer and decreased cost for the consumers (i.e., the demand side is “price-maker” and no longer “captive” to the retail prices). 3) Designing a dynamic pricing mechanism using demand price-sensitivity models at the retail market leads to higher correlation among the retail and wholesale markets, which is a step towards reducing the barrier between these two sectors.

This problem is addressed in Chapter 3.

Objective III: MG Power Management

Goal: Address the problem of cooperative resource allocation within MGs, considering different parties with different sets of objective function, using an agent-based model and the concept of NBS.

Hypothesis: A distributed bargaining framework is capable of finding a unique solution to the power management problem of single MGs. This solution is Pareto-

efficient, and introduces a fair balance between the objective functions of different agents. The agents can cooperatively find this solution in real-time.

This problem is addressed in Chapters 4 and 5.

Objective IV: Market-Based Multi-MG Systems

Goal: Generalize the distributed bargaining framework proposed in objective III to solve the cooperative power management of multiple neighboring MGs in a regional distribution system. The behavior of this MG-based distribution system needs to be studied in the retail market, under dynamic pricing. Use a dynamic pricing mechanism to indirectly control the power exchange between the distribution system and the main grid.

Hypothesis: 1) Using a distributed optimization framework and the concept of bargaining game, a market-based control system can be designed through which different constraints at different levels can be maintained in system operation while obtaining a fair balance in pay-off functions of different agents. 2) Employing a distributed market-based mechanism, the aggregate behavior of MGs can be indirectly controlled by finding the “correct” price signal. This correct price signal can compensate for system disturbances (e.g., unplanned MG islanding) in real-time by employing other available resources. In this way, the self-healing capability of the distribution system is effectively employed to lower cost of system operation. 3) The distributed bargaining system is able to reach the global optima of the decision model (as calculated by conventional optimization models) in a shorter span of time, compared to central optimization methods.

This problem is addressed in Chapter 6.

Objective V: Resiliency-Aware Distribution Systems

Goal: Introducing a resiliency-aware functionality into the proposed decision model in objectives III, and IV to prepare the distribution system against extreme events, most significantly blackout in the main grid after high impact weather-related events (e.g., storms and hurricanes). The resiliency-aware functionality needs to ensure that there is enough reserve in the system to ensure the continuation of system operation in the short term after blackouts. Also, other critical network constraints such as voltage magnitude and apparent power injection of the buses have to be integrated into the decision model to obtain a more thorough connection between the distributed optimization framework and the power network.

Hypothesis: 1) Introducing the resiliency-aware functionality leads to lower expected loss of load under extreme events. 2) Bus voltage levels can be kept within their acceptable operational boundaries through the proposed distributed decision model.

This problem is addressed in Chapter 7.

Dissertation Structure

Problem Hierarchy and Flow

Different problems addressed in this dissertation are connected together through a problem hierarchy, which is shown in Fig. 1.11. While Chapter 2 covers agent-based modeling at the wholesale level, the rest of the dissertation is concentrated on retail sector. Hence, Chapters 3, 4, 5, 6, and 7 address efficient agent-based resource allocation and optimal pricing techniques in electric distribution systems considering different perspectives (e.g., peak reduction, profit maximization, and self-healing and resiliency enhancement). In general, a common theme among these

different problems is that the proposed solutions are MAS-based and within the area of transactive control. Another unifying aspect among these chapters is the use of two game theoretic solution concepts, NE and NBS, to design and describe agent-based systems. In Chapter 2, NE is used for describing the outcome (equilibrium) of wholesale markets, and, the concept of NBS is used in Chapters 4, 5, 6, and 7 to design a cooperative distributed power management mechanism for distribution systems.

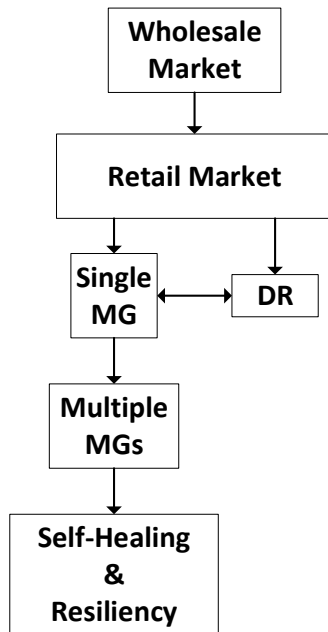


Figure 1.11: Dissertation problem hierarchy

The problems addressed in this work can be categorized into two main parts: 1) the problems related to the wholesale market (Chapter 2), and 2) the problems related to the retail market (Chapters 3, 4, 5, 6, and 7). In the first part, the aim of the dissertation is modeling competition between GenCos in the wholesale market. In the second part, we investigate resource allocation and power management techniques in distribution systems, in the context of retail markets. Hence, the problems in

the second part can be classified into two levels: level 1) the problem of dynamic energy pricing by a utility company at different stages using a data-driven approach (Chapters 3, and 6), and level 2) the problem of controlling different types of resources in the distribution system in response to the price signal received from the utility company. Different types of resources have been considered at this level: DR resources (Chapter 3), and MGs (Chapters 4, 5, 6, and 7). The flow of the problems is shown in Fig. 1.12.

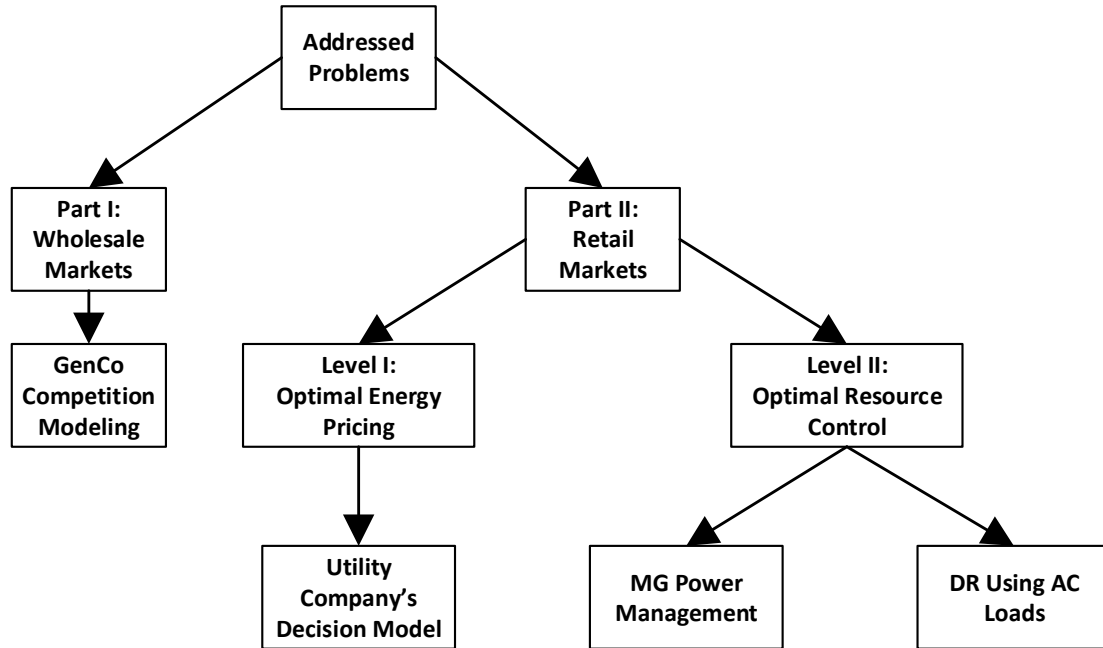


Figure 1.12: Dissertation problem categorization

Author's Published Works

The different chapters of the dissertation are composed of the author's published works. The complete list of the author's publications during his PhD studies and the chapters in which these articles appear are as follows:

Peer-reviewed journal papers:

- **Chapter 2:** K. Dehghanpour, H. Nehrir, J. Sheppard, and N. Kelly. Agent-based modeling in electrical energy markets using dynamic Bayesian networks. *IEEE Trans. Power Syst.*, 31(6):4744-4754, Nov. 2016.
- **Chapter 3:** K. Dehghanpour, H. Nehrir, J. Sheppard, and N. Kelly. Agent-based modeling of retail electrical energy markets with demand response. To appear in *IEEE Trans. Smart Grid*.
- **Chapter 5:** K. Dehghanpour and H. Nehrir. Real-time multiobjective microgrid power management using distributed optimization in an agent-based bargaining framework. To appear in *IEEE Trans. Smart Grid*.
- **Chapter 6:** K. Dehghanpour and H. Nehrir. An agent-based hierarchical bargaining framework for power management of multiple cooperative microgrids. To appear in *IEEE Trans. Smart Grid*.
- **Chapter 7:** K. Dehghanpour and H. Nehrir. A market-based resilient power management technique for distribution systems with multiple microgrids using a multi-agent system approach. Under review in *Electric Power Components and Systems*.
- K. Dehghanpour, C. Colson, and H. Nehrir. A survey on smart agent-based microgrids for resilient/self-healing grids. *Energies*, 10(5):620, May 2017.

Peer-reviewed conference papers and newsletter articles:

- **Chapter 4:** K. Dehghanpour and H. Nehrir. Intelligent microgrid power management using the concept of Nash bargaining solution. *Intelligent Systems Applications to Power Systems (ISAP)*, San Antonio, TX, 2017.

- A. Klem, K. Dehghanpour, and H. Nehrir. Primary frequency regulation in islanded microgrids through droop-based generation and demand control. *Intelligent Systems Applications to Power Systems (ISAP)*, San Antonio, TX, 2017.
- K. Dehghanpour and H. Nehrir. Distributed multi-agent system approaches for microgrid power management. *IEEE Smart Grid Newsletters*, Feb. 2017.
- A. Klem, H. Nehrir, and K. Dehghanpour. Frequency stabilization of an islanded microgrid using droop control and demand response. *North American Power Symposium (NAPS)*, Denver, CO, 2016.
- K. Dehghanpour and H. Nehrir. Wind power forecasting: comparing two statistical signal processing algorithms. *North American Power Symposium (NAPS)*, Charlotte, NC, 2015.

AGENT-BASED MODELING IN ELECTRICAL ENERGY MARKETS USING
DYNAMIC BAYESIAN NETWORKS

Contribution of Authors and Co-Authors

Manuscript in Chapter 2

Author: Kaveh Dehghanpour

Contributions: Developed and tested the agent-based decision model for the wholesale market, and prepared the manuscript.

Co-Author: Hashem Nehrir

Contributions: Supervised the overall flow of the project, and provided important insight on numerical studies and interpretation of the results. Aided in the preparation of the manuscript.

Co-Author: John Sheppard

Contributions: Provided important insight on machine-learning-based techniques and interpretation of results. Aided in the preparation of the manuscript.

Co-Author: Nathan Kelly

Contributions: Collaborated with the author for performing simulations.

Manuscript Information Page

Kaveh Dehghanpour, Hashem Nehrir, John Sheppard, and Nathan Kelly

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Abstract

Due to uncertainties in generation and load, optimal decision making in electrical energy markets is a complicated and challenging task. Participating agents in the market have to estimate optimal bidding strategies based on incomplete public information and private assessment of the future state of the market, to maximize their expected profit at different time scales. In this paper, we present an agent-based model to address the problem of short-term strategic bidding of conventional generation companies (GenCos) in a power pool. Based on the proposed model, each GenCo agent develops a private probabilistic model of the market (using dynamic Bayesian networks), employs an online learning algorithm to train the model (sparse Bayesian learning), and infers the future state of the market to estimate the optimal bidding function. We show that by using this multiagent framework, the agents will be able to predict and adapt to an approximate Nash equilibrium of the market through time using local reasoning and incomplete publically available data. The model is implemented in MATLAB and is tested on four test case systems: two generic systems with 5 and 15 GenCo agents, and two IEEE benchmarks (9-bus and 30-bus systems). Both the day-ahead (DA) and hour-ahead (HA) bidding schemes are implemented. The results show a drop in market power in the 15-agent system compared to 5-agent system, along with a Pareto superior equilibrium in the HA scheme compared to the DA scheme, which corroborates the validity of the proposed decision making model. Also, the simulations show that introduction of an HA decision making stage as an uncertainty containment tool, leads to a more stable and less volatile price signal in the market, which consequently results in flatter and improved profit curves for the GenCos.

Introduction

Unbundling of the electrical power supply industry and the introduction of market-based energy management logic into power systems has created an interactive system of decision-making-agents that seek to optimize their local objectives. In this context, in oligopolistic markets (i.e., a market with a few dominant firms), privately-owned generation companies (GenCos) try to maximize their expected profit from sales of energy to the consumers by bidding strategically in the market. Thus, GenCos exercise market power to affect the state of the energy market to their benefit.

However, power markets are abounded with uncertainty: intermittent renewable energy resources, and variable electrical load are two main sources of uncertainty. Moreover, each agent, by affecting the outcome of the market, is a source of uncertainty to its competitors. Hence, the problem of optimal decision making by participating agents in the market turns out to be a complex issue that has attracted considerable scientific interest in the past decade.

Strategic bidding in pool-based energy markets has been studied in the literature using the concepts of game theory. It has been shown that the oligopolistic energy markets can be modelled using bi-level optimization problems [116, 205]. At the top level, GenCos pursue the maximization of their profit functions, while at the lower level the Independent System Operator (ISO) agent solves a social welfare maximization problem to clear the market. Thus, the higher level optimization problems are constrained by the lower level problem. If the lower level problem is convex it can be replaced by its Karush-Kuhn-Tucker optimality conditions (KKT), which results in an Equilibrium Problem with Equilibrium Constraints (EPEC), which is a system of coupled Mathematical Programs with Equilibrium Constraints (MPEC) [69, 122]. The solution of EPEC would be the Nash Equilibrium (NE) [101]

of the energy market, which is a strategy profile of the agents from which none has any incentive to deviate unilaterally. The EPEC has been described analytically as a Stackelberg game with several leaders (GenCos) and one common follower (ISO) [82]. Many papers are dedicated to solving this system of nested optimization problems. Different approaches have been employed to simplify and find the equilibrium of the market: diagonalization [86, 98], binary expansion [12, 163], particle swarm optimization [231], variational inequality techniques [9, 208], information gap decision theory [99], polynomial equations [224], and the penalty interior point algorithm [82] are some of the tools that have been used in previous works. While these papers provide invaluable analytical insight on energy markets, they do not study the details of agent-based temporal learning process under uncertainty and incomplete information that leads to the market equilibrium.

Several papers have addressed the application of multiagent system (MAS) theory to energy markets. A remarkable review is presented in [210], in which the shortcomings of analytical approaches are pointed out. In [25], a rule-based naïve reinforcement learning (RL) algorithm is employed for each agent to search separately for optimal bidding strategies. In [145], an RL-based day-ahead (DA) bidding procedure for GenCos is proposed, based on discrete Markov decision processes. This method has been applied in [146] to study the effects of water shortage on electric power generation. Another RL scheme is introduced in [179] to study the dynamics of forward and spot markets. The effects of initial belief of the agents employing RL on the outcome of energy market is studied in [14]. As another RL-based technique, Q-learning is used in [227] to implement an agent-based model for energy markets. An interesting recently published work employs a multi-layer agent-based model to study the energy markets, considering the uncertain behavior of competitors [182]. This paper relies on probabilistic scenario generation and stochastic programming.

Stochastic programming is also used in [183] in combination with a branch-and-bound method for uncertainty assessment in the market. Agent-based optimal decision making in energy markets using numerical sensitivity analysis is proposed in [126].

Previous works on agent-based decision making in energy markets have mostly relied on reinforcement learning and stochastic programming to develop agent-level decision making models [193]. However, a shortcoming of these works is their dependence on discretizing the space of states and actions of agents. This on one hand, might lead to suboptimal solutions and on the other hand, introduces a limitation on applicability and scalability of the models. One shortcoming of the methods that are based on stochastic programming is their dependence on probability density functions that are non-stationary and hard to obtain [61]. Also, the integration of forecasting tools has been mostly ignored.

In this paper, we present a novel probabilistic model for GenCos' optimal decision making in energy markets. The agent-based reasoning apparatus is based on a Dynamic Bayesian Network (DBN) representation [142] where Sparse Bayesian Learning (SBL) is employed for model training. DBNs provide a natural and efficient framework to study reasoning under uncertainty; DBNs can be scaled to include a large number of random variables, if necessary. Thus, they have been adopted here for modeling agents' behavior in electrical energy markets. The presented DBN-based model constitutes the belief system of agents on the state of the market. This belief system is updated constantly through participation in the DA and HA energy markets. Each agent, using its private belief system develops offer curves according to a Linear Supply Function Equilibrium (LSFE) model [164,199], which provides an efficient and realistic model of behavior of GenCos in the market.

Two sources of uncertainty are considered in this paper: electrical load, and GenCo competitors' behavior. The electrical demand side is assumed to be inelastic.

Real load data from the Pennsylvania-New Jersey-Maryland (PJM) market is fed to the market model to simulate the temporal changes of electrical demand [165]. To represent and predict the behavior of competing GenCos, a Residual Demand Curve (RDC) is generated for each agent at each time step [4, 11]. Since the agents do not have access to the cost functions and decisions made by competitors, they have to rely on incomplete publicly available data (which is assumed to be the aggregate demand and supply curves published by the ISO) to construct their individual RDC. Both the load and RDC prediction functionalities are integrated into the DBN-based belief system of the agents.

The DBN-based decision making model provides adaptive agent behavior through variable and uncertain conditions in the market. An advantage of the proposed model is that it is based on continuous valued variables; hence, complexities pertaining to discretization and the possibility of suboptimal solutions are avoided. Another advantage of the DBN-based model is that the introduced probabilistic decision making tool is free and independent of any assumptions on probability density functions of the variables of the energy market; hence, avoiding the shortcoming of stochastic programming.

To summarize, the main contributions of this paper are as follows:

- To provide an agent-based decision making tool for energy markets, using probabilistic graphical models. Specifically, a dynamic Bayesian network is selected as the tool that is most fit for the task of modeling the belief systems of GenCos, as explained later in the paper (Section III).
- To avoid discretization of decision/action space, we have employed sparse Bayesian learning to train the dynamic Bayesian networks for each agent. Also, using the proposed belief system, particle-based sampling is employed

for forecasting.

The rest of the paper is constructed as follows. In Section II, the basics of the agent-based model are explained. In Section III the DBN-based belief system of GenCo agents, along with learning and inference schemes are described. Simulation results are presented and discussed in Section IV. Conclusions and future research directions are reported in Sections V, and VI, respectively.

Structure of the Agent-Based System

The energy market under study is formulated into a hierarchical multiagent system, as shown in Fig. 2.1. At the top level, GenCo agents compete with each other to supply the inelastic demand by submitting optimal bidding functions. There is no direct communication link among GenCo competitors, and any interaction among them takes place through market outcome and thus, is indirect by nature. At the bottom level, the ISO agent clears the market based on the received bidding functions. The details of the agents functions are discussed below. Also, the DA/HA bidding procedure of the GenCo agents is introduced for market modeling.

GenCo Agents Model

The cost function (C_{gi}) of the i^{th} GenCo agent is modeled as a quadratic function of its output power (P_i), as given in (2.1). Fixed cost elements are ignored. Also, the power production of the GenCo is bounded by its maximum power capacity (P_{max}^i), which defines the feasible operational region of the GenCo.

$$C_{gi}(P_i) = a_i P_i + \frac{1}{2} b_i P_i^2 \quad (2.1)$$

$$0 \leq P_i \leq P_{max}^i.$$

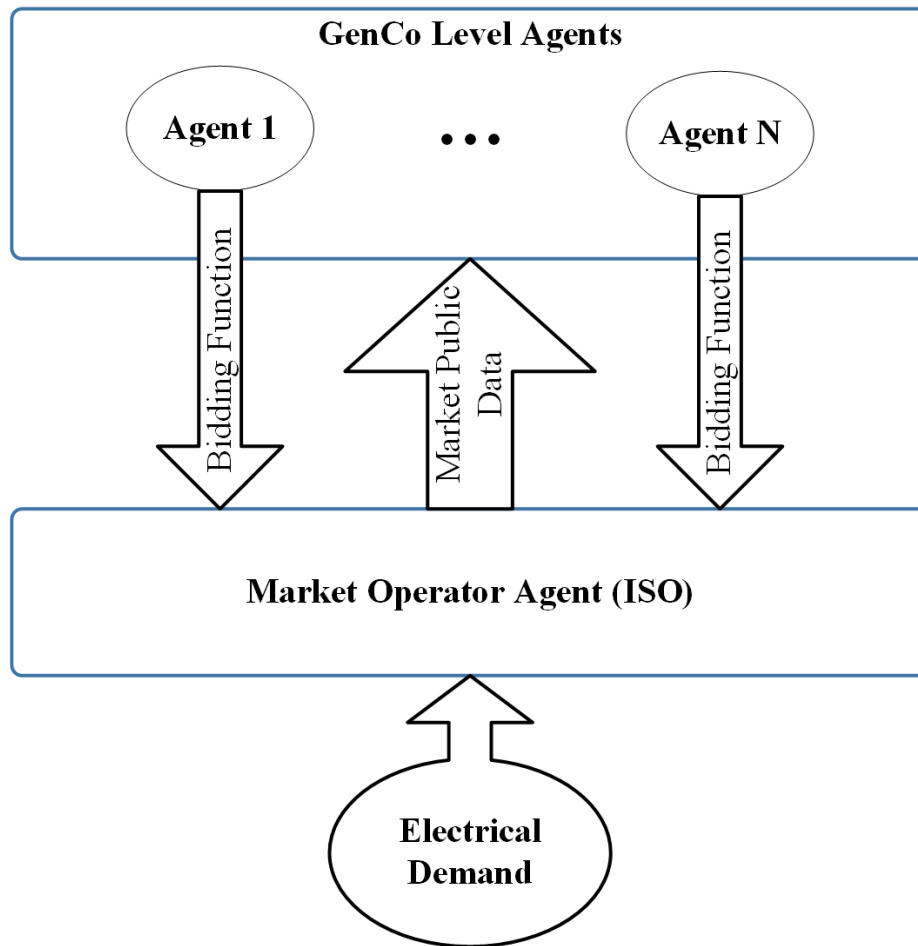


Figure 2.1: Structure of the multiagent market model

The marginal cost function of the i^{th} agent (MC_{gi}) is therefore, a linear function of output power.

$$MC_{gi}(P_i) = a_i + b_i P_i \quad (2.2)$$

In a purely competitive market the GenCos act as price-takers and bid their marginal cost functions to the market [212], whereas in an oligopolistic market, GenCo agents submit bidding functions that deviate from their marginal cost curves, in order to maximize their expected profit. Price-making GenCos exercise some levels of market power. In this paper we have adopted LSF model for GenCos' bidding procedure. Thus, the submitted bidding function (B_{gi}) to the ISO agent is a linear function of output power of the GenCo, as follows:

$$B_{gi}(P_i) = \hat{a}_i + \hat{b}_i P_i \quad (2.3)$$

where, the coefficients of $B_{gi}(P_i)$ (i.e., \hat{a}_i , and \hat{b}_i) are assigned by the i^{th} GenCo, to maximize its expected profit level. Therefore, the goal of the strategic bidding problem is to parameterize the bidding functions of the GenCos optimally. In this paper, we have used what is known as intercept-parameterization [14] (i.e., the slope of $B_{gi}(P_i)$ is kept equal to the slope of $MC_{gi}(P_i)$, and the intercept with the price axis is modified). The merits of intercept-parameterization are discussed in [101]. Hence, $B_{gi}(P_i)$ is determined as follows:

$$B_{gi}(P_i) = a_i + O_i + b_i P_i \quad (2.4)$$

where, the parameter O_i in (2.4) determines the level of deviation of $B_{gi}(P_i)$ from $MC_{gi}(P_i)$, and is referred to as strategic parameter for the i^{th} GenCo agent. Thus, the objective of each GenCo agent would be to maximize its profit level (Π_{gi}) at each

round of bidding by modifying the strategic parameter, subject to power constraints:

$$\begin{aligned} \max_{O_i} \Pi_{gi} &= \{\lambda(O_i, \mathbf{O}_{-i}) \cdot P_i - C_{gi}(P_i)\} \\ \text{s.t. } &0 \leq P_i \leq P_{max}^i \end{aligned} \quad (2.5)$$

where, λ is the energy price, which is a function of both the i^{th} GenCo's strategic parameter and vector of strategic parameters of competitors (\mathbf{O}_{-i}).

To provide a base for individual GenCo's self-scheduling behavior, the concept of RDC is employed. RDC provides a measure of dependence of market status merely based on a single player's actions by fixing the behavior of competitors. Using the aggregate supply function of the market and the demand level, each GenCo can construct its individual RDC as discussed in [198]; and since the basic assumption in this paper is that the only published data to GenCos is the aggregate supply and demand functions of the market at each round, we are able to employ the concept of RDC. Note that RDC can only be constructed after the market is cleared; thus, the agents have access to RDCs of the previous rounds of auction. As a part of the optimal decision making process, one goal of the learning model proposed in this paper is to predict the RDC for the future round of bidding.

The RDC of the i^{th} agent is a decreasing nonlinear function of the generated output power. However, in order to be able to employ RDCs in the agents belief systems, they have to be parameterized. For that purpose, simple linear regression is used to present a linear estimation of RDC, denoted by λ_{gi} , as in (2.6).

$$\lambda_{gi}(P_i) = \alpha_i P_i + \beta_i. \quad (2.6)$$

The slope of linearized RDC is negative ($\alpha_i < 0$). By intersecting $\lambda_{gi}(P_i)$ and

$B_{gi}(P_i)$, the approximate clearing price (λ^*) and dispatched generation level for the i^{th} agent (P_{gi}^*) are obtained (note that the approximation is due to using a linear representation for the RDC.).

$$\lambda^* \approx \frac{a_i \alpha_i + O_i \alpha_i - b_i \beta_i}{\alpha_i - b_i} \quad (2.7)$$

$$P_{gi}^* \approx \frac{a_i + O_i - \beta_i}{\alpha_i - b_i}. \quad (2.8)$$

By inserting (2.7) and (2.8) into equation (2.5) and simplifying it, we can formulate Π_{gi} as a quadratic concave function in O_i . The value of the strategic variable for the i^{th} agent at which the unique maximum profit level (Π_{gi}^{max}) is achieved is denoted by O_{mi} , which along with Π_{gi}^{max} are obtained by solving $\partial \Pi_{gi} / \partial O_i = 0$. The results are as follows:

$$O_{mi} \approx \frac{\alpha_i(\beta_i - a_i)}{2\alpha_i - b_i} \quad (2.9)$$

$$\Pi_{gi}^{max} \approx \frac{(\beta_i - a_i)^2}{2(b_i - 2\alpha_i)}. \quad (2.10)$$

As can be seen from (2.9), as the sensitivity of the market price to the actions of the i^{th} agent (i.e., α_i) approaches zero, the GenCo becomes a price-taker, and therefore, O_{mi} converges to zero, resulting in truthful bidding. This is in accordance with our expectation.

While (2.9) provides a deterministic relationship between the optimal value of strategic variable and model parameters, it cannot be used directly for GenCo decision making. The reason for this is that the actual RDC is nonlinear; thus, using parameters of its linear approximation (i.e., α_i , and β_i) to obtain O_{mi} , leads to additional numerical errors. To overcome this problem, we have introduced the

optimal strategic parameter as another random variable inside the belief system of each agent (refer to Section 2). Numerical experiments show that employing probabilistic inference to obtain estimations of optimal value of strategic parameter reduces numerical errors considerably.

With this introduction on GenCo agents models, the step-by-step algorithm performed by each agent separately is as follows:

1. After the market is cleared at time t :
 - Construct the RDC for the latest round of auction using publicly available aggregate demand and supply functions.
 - Use the constructed RDC to obtain the optimal value of the strategic parameter by creating a profit curve as a function of $O_i(t)$.
 - Use linear regression to parameterize the RDC and obtain $\alpha_i(t)$, and $\beta_i(t)$.
 - Use the obtained values of $\alpha_i(t)$, $\beta_i(t)$, $O_{mi}(t)$, and system demand at time t (denoted by $D(t)$), to update agent data history.
 - Employ the updated data history and perform SBL to update the DBN-based belief system (Section 2).

2. DA/HA optimal bidding for the future round of market at time $t + 1$:
 - Perform probabilistic particle-based forward sampling over the DBN-based belief system (Section 2) to predict the values of variables ($\alpha_i(t+1)$, $\beta_i(t+1)$, optimal $O_i(t+1)$, and $D(t+1)$) for the future round of DA/HA auction.
 - Construct the bidding function using the predicted value for the optimal strategic parameter. Submit the bidding function to the ISO agent.

We will show that using the procedure above, each agent is able to maximize its profit in real-time with acceptable errors. Therefore, this distributed system of

interactive decision makers approaches a Nash equilibrium (i.e., each player is able to predict its best response to competitors).

ISO Agent Model

The task of the ISO agent is to perform an optimal generation resource allocation to supply the electrical demand on an hour-by-hour basis. Hence, the ISO runs an economic dispatching problem to maximize social welfare (i.e., to minimize total production cost) based on the received bidding functions from GenCo agents.

$$\min_{P_1, \dots, P_N} \sum_{i=1}^N (\hat{a}_i P_i + \frac{1}{2} \hat{b}_i P_i^2) \quad (2.11)$$

$$\text{s.t. } \sum_{i=1}^N P_i = D, 0 \leq P_i \leq P_{max}^i, \forall i = 1, \dots, N$$

In this paper, the ISO agent uses the lambda-iteration method [215] to solve the economic dispatching problem. The inputs of the ISO agent are GenCo agents' bidding curves and the real-time electrical demand. Note that the ISO agent does not have access to GenCo agents' actual marginal cost functions. As mentioned earlier, for the electrical demand, actual hourly data (normalized by maximum available generation capacity) from the PJM market is employed [165]. After normalization, the load signal is fed directly to the model in simulations.

When the GenCos submit their offers, the ISO solves (2.11) for real-time load to clear the market. Then it publishes (publicly) the energy price, aggregate supply curve, and real-time demand. Details of individual GenCos' bidding functions are not exposed to competitors. Since we have ignored the effects of the transmission system on the energy market, the energy price is the same for all GenCo agents.

DA/HA Bidding Procedures

Note that the bidding process in the market takes place on two distinct but closely related time scales: DA market and HA market. Hence, we need to study the overall behavior of the energy market on these two scales. The mechanisms of HA/DA stages of energy markets have been described in [24] and [21]. As demonstrated in these works, as the GenCos move closer to real-time they need to compensate the power mismatch created by the errors of forecasting tools in the DA stage. In this paper, we study the interaction and effects of introducing the HA stage into the energy market, using the proposed DBN-based decision making model.

GenCo agents employ two private databases to keep their belief systems updated: the DA database and the HA database. The DA database is decomposed into 24 sections, with each section corresponding to a certain hour in the day. This has been done because of the high correlation among the load samples with a 24-hour time difference, which makes the daily load profile semi-periodic. Hence, decision making for a certain hour of the day in the DA market is based on the data history of the same hour on previous days (in this study, up to the past 300 days). Note that weekly, seasonal, and annual trends of electrical load are ignored in this paper. The HA database is composed of the HA data history of the previous hours of the market up to the most recent hours.

At each hour of the day, each GenCo agent submits two bidding functions to the market: one bidding function is submitted to participate in the next incoming hour of the same day (i.e., HA bidding), and the second bidding function is submitted for participation in the energy market of that same hour in the next day (i.e., DA bidding). Note that the market is cleared using the predicted value of the load for each stage.

According to [21], the total amount of payment that the i^{th} GenCo receives in a

multistage market R_i (i.e., a market with both DA and HA stages), is as follows:

$$R_i = P_i^{DA}\lambda^{DA} + (P_i^{HA} - P_i^{DA})\lambda^{HA} + (P_i^{RT} - P_i^{HA})\lambda^{RT} \quad (2.12)$$

where, P_i^{DA} , P_i^{HA} , and P_i^{RT} are the scheduled power of the i^{th} unit in DA, HA, and real time markets, respectively; λ^{DA} , λ^{HA} , and λ^{RT} are the energy prices corresponding to these different stages. On the other hand, the payment amount in a single-stage market (i.e., DA stage only) is modified as follows:

$$R_i = P_i^{DA}\lambda^{DA} + (P_i^{RT} - P_i^{DA})\lambda^{RT} \quad (2.13)$$

DBN-Based Optimal Decision-Making

Probabilistic graphical models (PGMs) offer useful tools for representing and analyzing statistical relationships and dependencies among random variables. Bayesian networks, Markov networks, Hidden Markov Models (HMM), etc. [142] are a few variations of PGMs that have been studied and used in different applications. A thorough introduction on PGMs can be found in [107].

DBNs are a category of directed PGMs that are able to capture the temporal evolution of random variables; thus, they are often a good fit to model systems with discrete-time stochastic processes [142]. DBNs can be thought of as a generalization of both static Bayesian networks and HMMs: while static Bayesian networks are a class of multivariate directed PGMs, they are unable to represent time-dependency of random variables, and are consequently not fit to model random processes. On the other hand, HMMs are a category of DBNs in which the dynamic nature of the model is preserved; however, HMMs are conventionally best fit to model univariate systems (i.e., one random variable for the hidden state chain and one for the output

chain). DBNs provide a general framework that address the shortcomings of static Bayesian networks and HMMs.

We model the belief system of each GenCo using DBNs. The belief system embodies each agents probabilistic perception of its environment, which is the energy market (including the competitors, the ISO agent, and uncertain demand). Thus, each GenCo develops a DBN-based private model of the market and keeps it updated at each time step. The DBN-based models are then used by each agent to predict the future state of the market and act accordingly.

A DBN is composed of several vertices that represent random variables, and directed edges among them, which represent probabilistic dependencies. A directed edge starts at a parent vertex and ends in a child vertex (Fig. 2.2). The parameter of the model associated with a particular parent-child structure is equal to the conditional probability distribution function (PDF) of the random variable corresponding to the child node, given the values of random variables corresponding to its parents. Also, the DBN spans time to model the temporal changes in variables (the same as HMM). To develop a DBN-based model we have to address three issues: structure learning (i.e., determining hidden/observable random variables, edges and their direction), parameter learning (i.e., finding the conditional PDFs corresponding to parent-child structures), and inference over future events (i.e., prediction).

Structure Selection

Since the number of variables considered in the proposed DBN-based belief system is low, the structure of the model is selected based on experiments and using statistical measures such as mutual information (MI). However, if in future developments of the model, the number of variables grows to be large, a thorough structure learning algorithm should be implemented. The proposed structure is

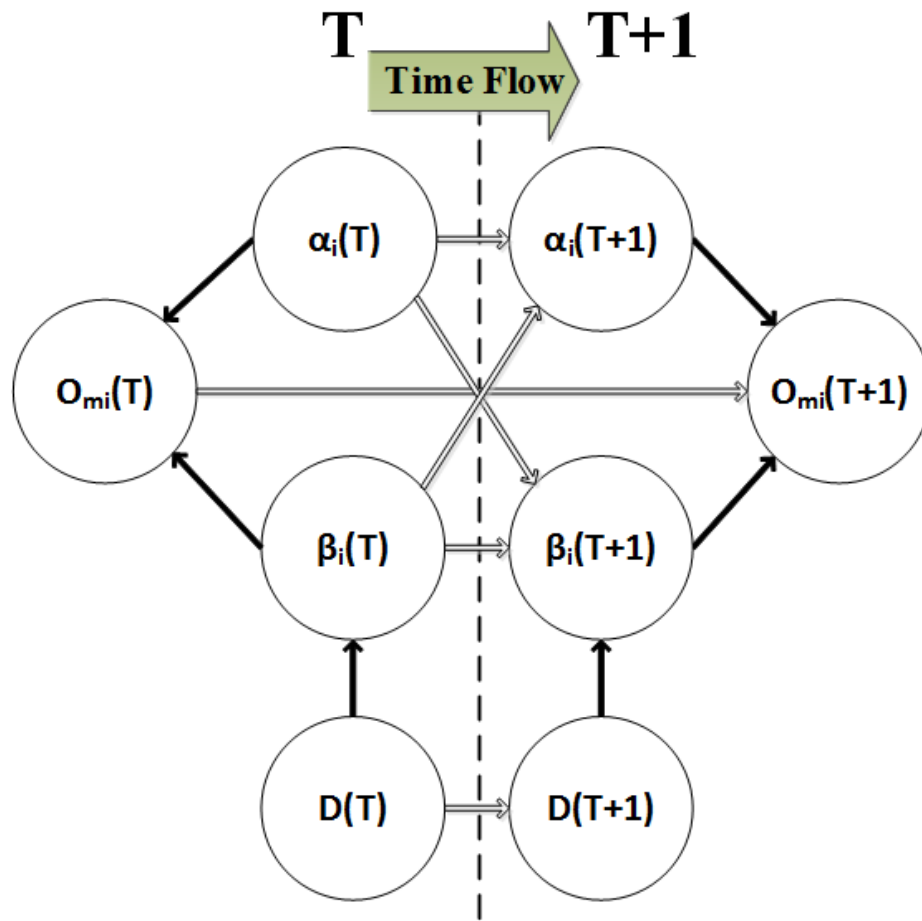


Figure 2.2: DBN-based belief system of GenCo agents

depicted in Fig. 2.2. As can be seen, the proposed DBN is a first-order Markov model with four variables at each time slice. The transition time step can be 1 hour or 24 hours, depending on the bidding horizon being HA or DA. This means that for DA bidding at a certain hour of the future day, the data history of that same hour on previous days are employed. On the other hand for HA bidding, the data for previous hours is used as the training set.

The random variables at each time slice of the belief system of i^{th} agent are: D (electrical demand), β_i (intercept of agents linearized RDC with price axis), α_i (slope of agents linearized RDC), and O_{mi} (optimal value of strategic parameter). As shown in Fig. 2.2, the electrical demand is not affected by market conditions (i.e., price-insensitivity); therefore, the value of load at the future time slice ($D(T + 1)$) is affected only by the demand level at present time slot $D(T)$. Note that each agent employs its private DBN-based belief system in the decision-making.

Since to the best of our knowledge, this structure has the best performance among the candidates, and the GenCos are assumed to be rational agents (i.e., the chances of making mistakes are ignored), all GenCos will use the same structure for decision making process.

Parameter Learning

Now that the structure of the graphical model is selected, the problem of parameterization should be addressed. Each local parent-child structure of the DBN (Fig. 2.3) represents a conditional PDF that has to be determined online. Note that all of the variables of the model are considered to be continuous; that is to maintain model precision and avoid difficulties pertaining to discretization, we keep the original continuous nature of the system.

As mentioned previously, Sparse Bayesian Learning (SBL) [195] is employed to

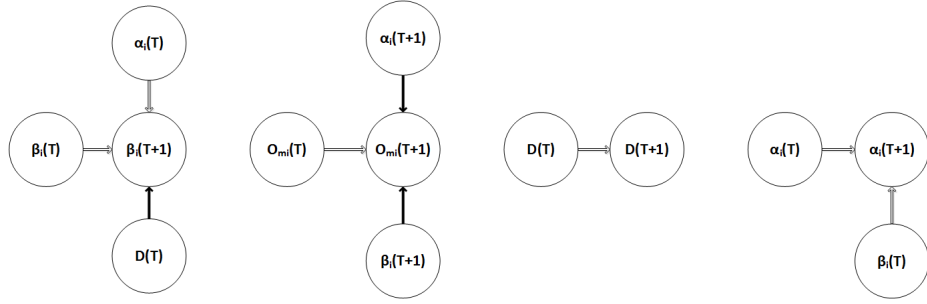


Figure 2.3: Local parent-child structures within the DBN

parametrize the DBN-based belief system. Thus, when the database of the agents are updated (i.e., when ISO publishes data to agents), SBL is applied to each of the local structures in Fig. 2.3, for the individual belief system of each separate agent to keep the overall belief systems updated.

SBL is a kernel-based learning algorithm which is also known as “relevance vector machine” [195]. The goal in SBL is to calculate the weights of the kernel functions, which for this project are selected to be Gaussians. A great advantage of SBL is its sparsity—only a subset of kernels have non-zero weights. As the learning process evolves, an increasing number of kernels tend to have weights with practically zero value. Therefore, using a pruning operation, we can omit the kernels that are not relevant to the learning process. The deletion of irrelevant kernels is a mechanism within SBL that prevents overfitting.

Given our training set $\{\mathbf{x}_n, t_n\}_{n=1}^N$ in which \mathbf{x}_n is the set of explanatory variables (i.e., parents) and t_n is the target variable (i.e., child variable), the kernel-based representation of target variable is shown below:

$$t_n = \sum_{i=1}^N w_i \cdot K(\mathbf{x}_n, \mathbf{x}_i) + w_0 + \epsilon_n. \quad (2.14)$$

Here, w_i s are the weights of the kernel functions $K(\mathbf{x}_n, \mathbf{x}_i)$, and ϵ_n is a noise process,

which is assumed to be a zero mean Gaussian process with variance σ^2 . Using this model, the objective of SBL is to estimate the weights of the kernel functions and the variance of the noise process. Note that the likelihood of the dataset can be written as a Gaussian function (since we have assumed that the distribution of noise is Gaussian):

$$p(\mathbf{t}|\mathbf{w}, \sigma^2) = (2\pi\sigma^2)^{-\frac{N}{2}} \exp\left\{-\frac{1}{2\sigma^2}\|\mathbf{t} - \Phi\mathbf{w}\|^2\right\} \quad (2.15)$$

where Φ is called the design matrix:

$$\Phi = \begin{bmatrix} 1 & K(\mathbf{x}_1, \mathbf{x}_1) & \cdots & K(\mathbf{x}_1, \mathbf{x}_N) \\ \vdots & \vdots & \ddots & \vdots \\ 1 & K(\mathbf{x}_N, \mathbf{x}_1) & \cdots & K(\mathbf{x}_N, \mathbf{x}_N) \end{bmatrix} \quad (2.16)$$

The prior distributions over the weights are selected to be independent zero-mean Gaussians:

$$p(\mathbf{w}|\alpha) = \prod_{i=1}^N \mathcal{N}(w_i|0, \alpha_i^{-1}) \quad (2.17)$$

where, α is the vector of hyperparameters, and is equal to the set of inverse variances of the kernel weights. As α_i gets larger and larger during the learning process, the corresponding kernel function gets more and more irrelevant and can be eliminated. To make predictions, we will be needing the posterior of the unknown parameters and hyperparameters given the observed target vector. The posterior is decomposed using the chain rule, as follows:

$$p(\mathbf{w}, \alpha, \sigma^2|\mathbf{t}) = p(\mathbf{w}|\mathbf{t}, \alpha, \sigma^2)p(\alpha, \sigma^2|\mathbf{t}). \quad (2.18)$$

The first term on the right hand side of (2.18) is the posterior distribution over the weights and can be calculated analytically. Using Bayes rule, the posterior

distribution is formulated into a Gaussian distribution with covariance matrix Σ and mean vector μ [195]. The second term on the right hand side of (2.18) can be replaced with a delta function that is nonzero only at the most probable values for the hyperparameters (σ_{MP}^2 and α_{MP}). Values of σ_{MP}^2 and α_{MP} have been calculated using expectation-maximization-based recursive estimations, to maximize the marginal likelihood function (different update rules are discussed in [195].) Thus, the parameter of a local structure in the DBN-based belief system with child variable X , and its parents $\mathbf{Pa}(X)$ is a Gaussian distribution, obtained as follows:

$$p(X|\mathbf{Pa}(X)) \sim \mathcal{N}(\mu^\top \Phi(\mathbf{Pa}(X)), \sigma_{MP}^2 + \Phi(\mathbf{Pa}(X))^\top \Sigma \Phi(\mathbf{Pa}(X))). \quad (2.19)$$

Inference

After the conclusion of the learning procedure at each time step, the agents perform probabilistic inference over variables of a future time slice. In other words, they predict the future state of the market to estimate the optimal value of the strategic variable for the future round of auction (next hour or next day).

In this paper, inference is accomplished using a particle-based forward sampling method [107]. The values of the variables at the current time slice are initialized as evidence (primary particles). Then, using the learned model parameters (i.e. conditional PDFs) we move along the directed edges of the DBN to obtain particles of the future time slice. This process is repeated 500 times. The mean of obtained particles is used as the predicted values for the variables in the future time slice. When the GenCos obtain an estimation of $O_{mi}(T+1)$ through probabilistic inference, they modify their bidding function accordingly and submit it to the ISO agent.

Decision Making Process

The DBN-based decision making process involves the two functionalities of learning and prediction (i.e., inference). Upon receiving the latest data samples from the most recent round of auction, first, each agent updates the conditional probability density functions corresponding to parent-child structures of the DBNs, employing SBL. These updated conditional PDFs represent the statistical affinities among the variables (i.e., α , β , D , and O). The final goal of the decision making problem is to find or estimate the optimal course of action for the future round of auction, at the HA or the DA look-ahead windows. Hence, the updated conditional PDFs are used to achieve this goal. Given the latest samples for the variables at the current time step, the future samples for the variables are extracted using a forward sampling method, employing the learned conditional PDFs. Considering the structure of the DBN (Fig. 2.2), the current samples of variables α , β , D serve as inputs to the decision making process and are used to generate the predicted samples for the same variables. Finally, the predicted samples for the input variables (at time $t + 1$) are employed to estimate the optimal course of action for the incoming round of auction (i.e., strategic parameter, O). The sampling process is performed repeatedly, as explained in the previous subsection, and the mean of the samples for the strategic parameter, O , is used as the forecasted optimal action, which determines the deviation from the marginal cost curve when bidding in the market. The algorithmic overview of the overall decision making process is presented in Section II of the paper. The agent-based decision making process is illustrated in Fig. 2.4, for one GenCo agent.

Agent's Decision Making Process

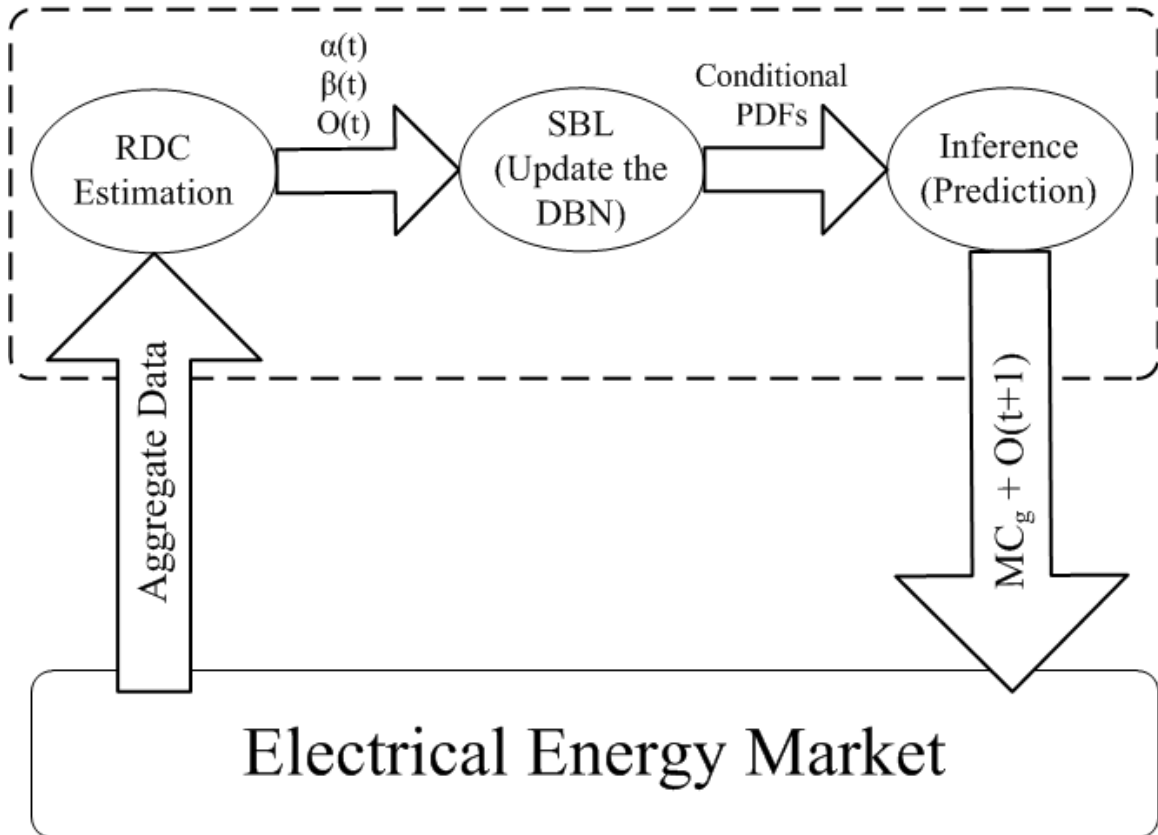


Figure 2.4: GenCos agent-based model

Numerical Experiments and Results

The proposed decision making model is tested in a MATLAB environment for three test cases: two systems with 5 and 15 GenCo agents, corresponding to energy markets with high and low market share concentration, and the IEEE 30-bus benchmark system. Both HA and DA bidding schemes are implemented in all the test cases. The proposed decision making model is tested in MATLAB environment for systems with 5 and 15 GenCo agents, corresponding to energy markets with high and low market share concentration. Both HA and DA bidding schemes are implemented. Thus, the behavior of the proposed model on different time scales and different market concentration levels is studied.

After the market is cleared, real-time optimal values of strategic parameters of each agent are obtained using real time RDC for each GenCo. The results are then compared with DBN-based DA/HA predictions to assess the performance of the decision making model.

Case Study I

Considering an HA bidding scheme for the system with 5 agents (cost parameters given in Table 2.2, Appendix section of the paper), the optimal real-time value of strategic parameter for one of the agents is depicted in Fig. 2.5, along with its DBN-based estimation. As can be seen, the DBN-based estimation follows the real-time optimal value with satisfactory precision (mean absolute error (MAE) of 3.83%). This implies that the DBN-based belief system can be employed for prediction of the result of HA market and optimal acting accordingly. Also, the results of the prediction of the other three variables of the belief system (α , β , and D) and their real-time values are shown in Figs. 2.6, 2.7, and 2.8, respectively. The MAE level of predictions for

these variables are below 3%.

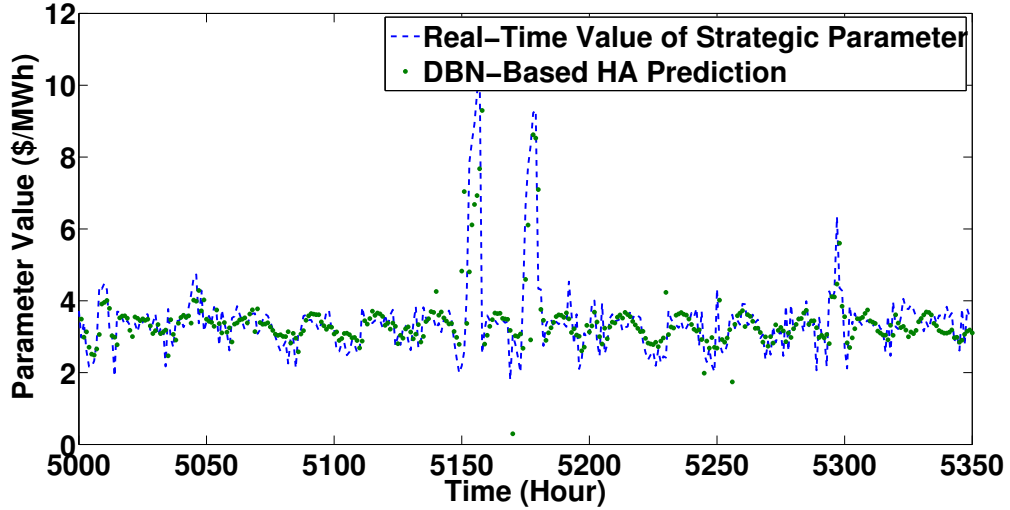


Figure 2.5: HA DBN-based strategic parameter prediction

The rest of the GenCo agents in the system show similar performance. As the real-time average optimal value of the strategic parameter approaches zero, the MAE increases (since the error normalizer tends to shrink to near zero values). This implies that, for agents that are not exercising market power (i.e. no tangible deviation from marginal cost), the DBN-based decision making procedure becomes less reliable. However, practically the average error values of O_{mi} prediction for all the agents are similar and around \$0.3/MWh.

Since the actions of all the agents are nearly optimal, the system approaches a NE. Thus, the DBN-based belief system enables the GenCos to predict the real-time market equilibrium and modify their actions to maximize their profit.

Case Study II

The decision making model is also tested on the 15-agent system for a DA bidding scheme (cost parameters given in Table 2.3, Appendix section of the paper).

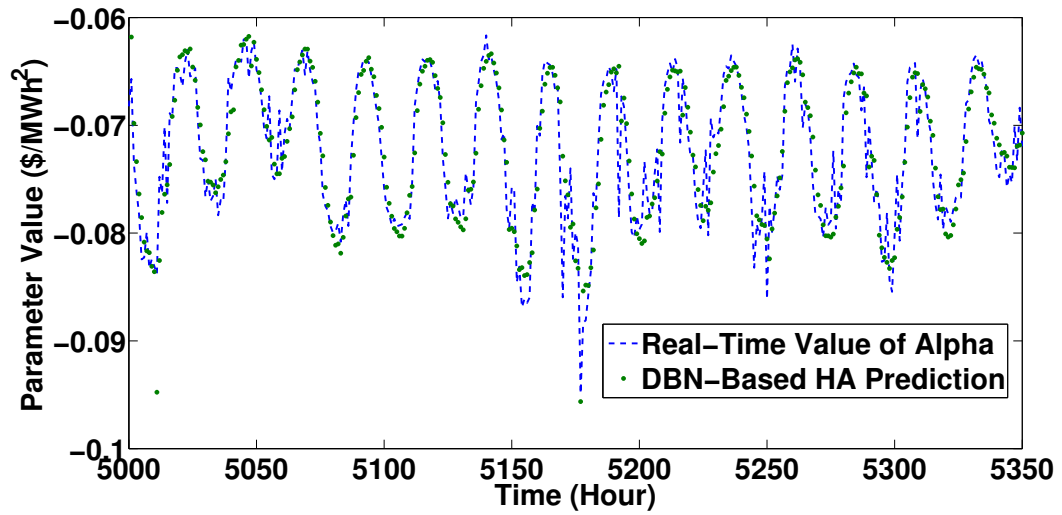


Figure 2.6: HA DBN-based Alpha parameter prediction compared

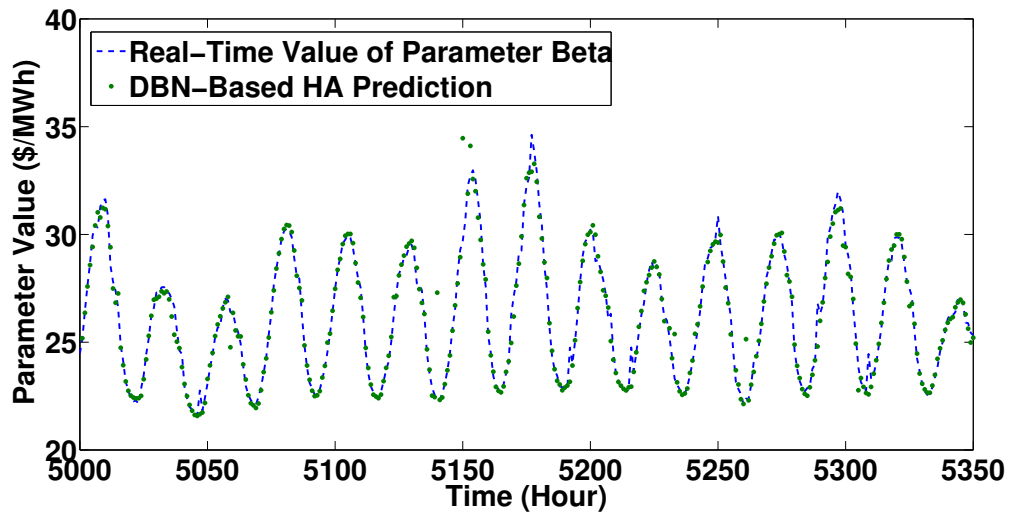


Figure 2.7: HA DBN-based Beta parameter prediction

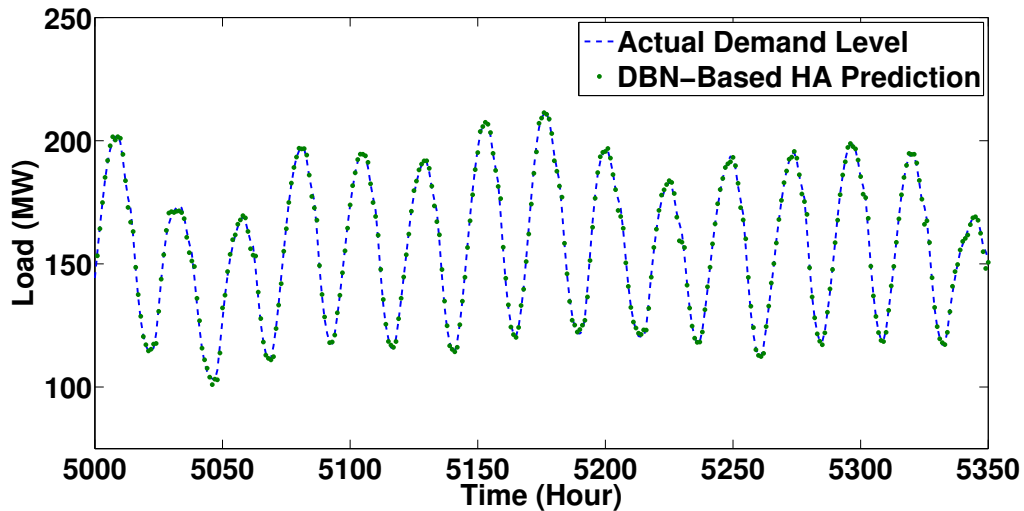


Figure 2.8: HA DBN-based demand prediction

As mentioned before, for DA bidding on a certain hour of the next day, the agents use the data history of the same hour on previous days to train their DBN-based private belief systems. Hence, each agent has 24 DBNs corresponding to each hour of the day. In Fig. 2.9, the result of prediction of O_{mi} is presented for one of the agents, on a certain hour of the day. The spikes on the curve correspond to an increase in the DA load profile for that hour of the day (Fig. 2.10). This implies that, as the demand increases, each GenCo's incentive to deviate from its marginal cost curve grows. The profit profile of the agent is depicted in Fig. 2.11. As shown here, the DBN-based strategic bidding leads to an increase in the real-time profit level and approximately reaches the real-time maximum possible profit. The DBN-based DA demand prediction outcome is shown in Fig. 2.10. Compared to HA load estimation with MAE of 2.34%, the MAE level of DA load forecasting increases to 7%.

Here again, all the agents show similar performance in prediction and decision-making; and since each agent is maximizing its profit at the same time with acceptable precision, the DBN-based distributed decision-making has led the multiagent system

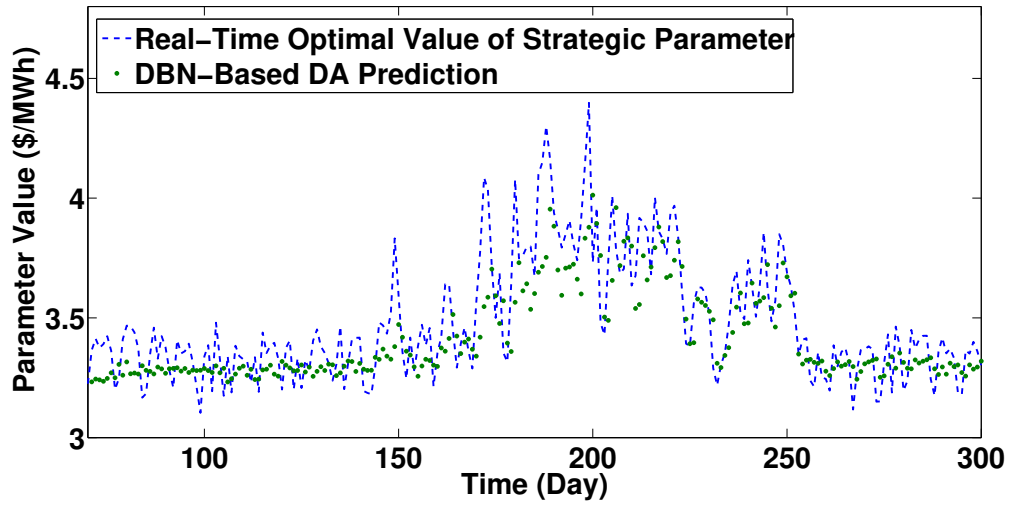


Figure 2.9: DA DBN-based strategic parameter prediction

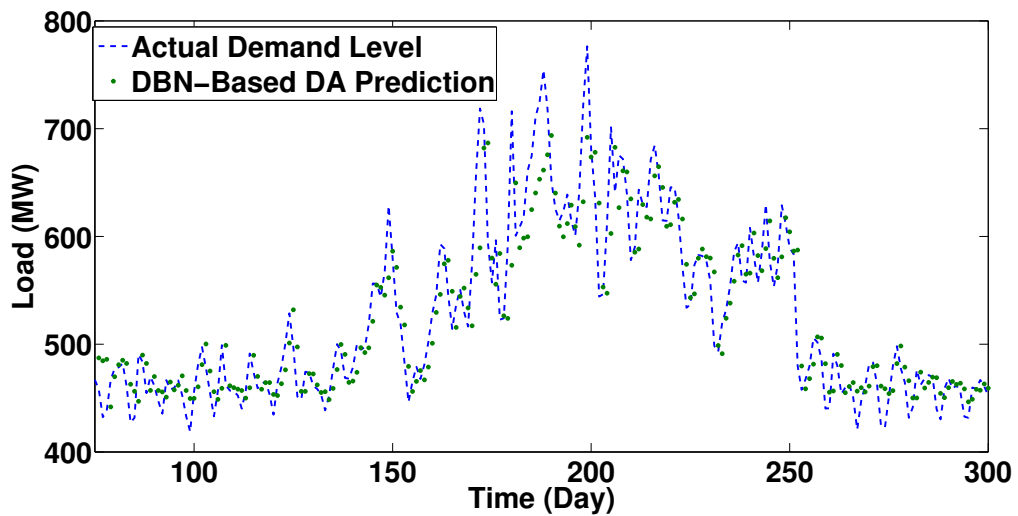


Figure 2.10: DA DBN-based demand prediction

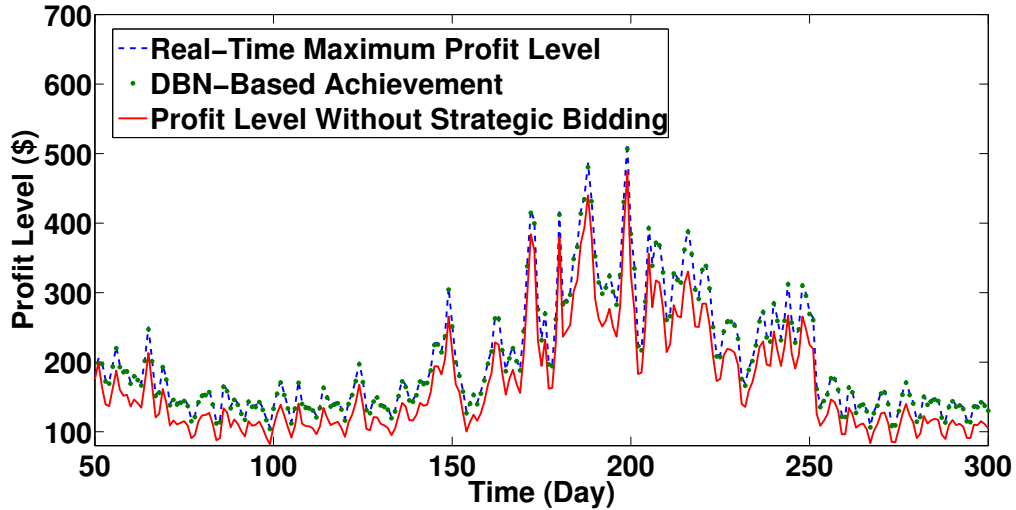


Figure 2.11: GenCo agent's DBN-based achieved profit level

to approach its NE.

Case Study III

The proposed decision making model is tested on the IEEE 9-bus system (consisting of three agents), as illustrated in Fig. 2.12. The cost data for the three GenCo agents in this system are provided in the Appendix section of the paper, Table 2.4 [120]. The final output variable (i.e., the strategic parameter) of the DBN for one of the agents of this system (with $a_i = \$1/MWh$, $b_i = \$0.24/MWh^2$, and $P_{max}^i = 120 MW$) as a function of time is depicted in Fig. 2.13. The MAE level is 4.95% and 11.24% for the HA and DA look-ahead times, respectively. Note that Fig. 2.13 shows the optimal course of action to be taken by the agent at each time step for the HA and DA cases. Hence, the agent determines its bidding function based on the predicted value of the strategic parameter at each time step. To further clarify the decision making process, we have shown the samples of the variables for the agent in Table 2.1, at $t = 5900 h$ and predictions for $t + 1 = 5901 h$. The samples at time

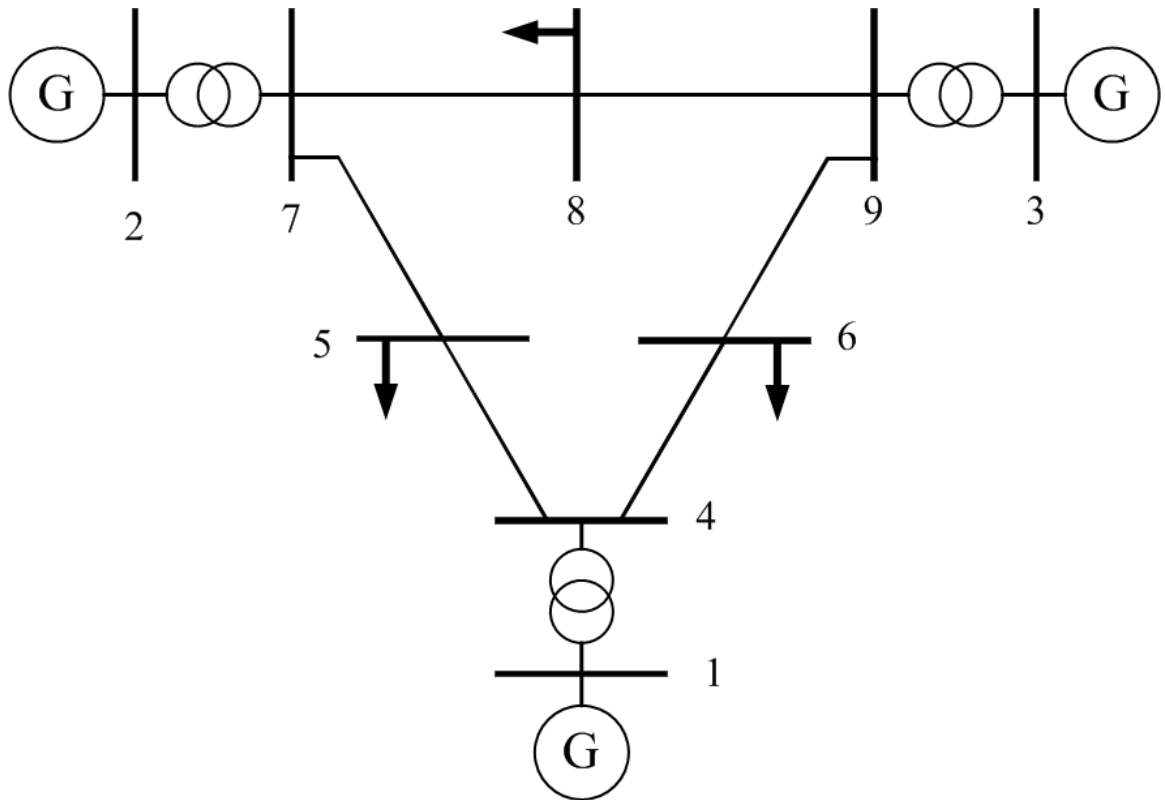


Figure 2.12: Structure of IEEE 9-bus system [120]

Table 2.1: Details of the Decision-Making Process

	$\alpha_i (\$/MWh^2)$	$\beta_i (\$/MWh)$	$D (MW)$	$O_i (\$/MWh)$
$t = 5900 \text{ h}$	-0.1091	76.3	435	16.36
HA prediction $t = 5901 \text{ h}$	-0.1095	73.1	415	15.7
RT values $t = 5901 \text{ h}$	-0.1081	72.8	433	15.67

t are used for updating the DBN and forecasting the values of the variables at time $t + 1$. The actual values of the variables at time $t + 1$ are given in the last row of the table. As can be seen, the HA predicted values for time $t + 1$ are close to their actual real-time values that are obtained after market clearance at that specific time.

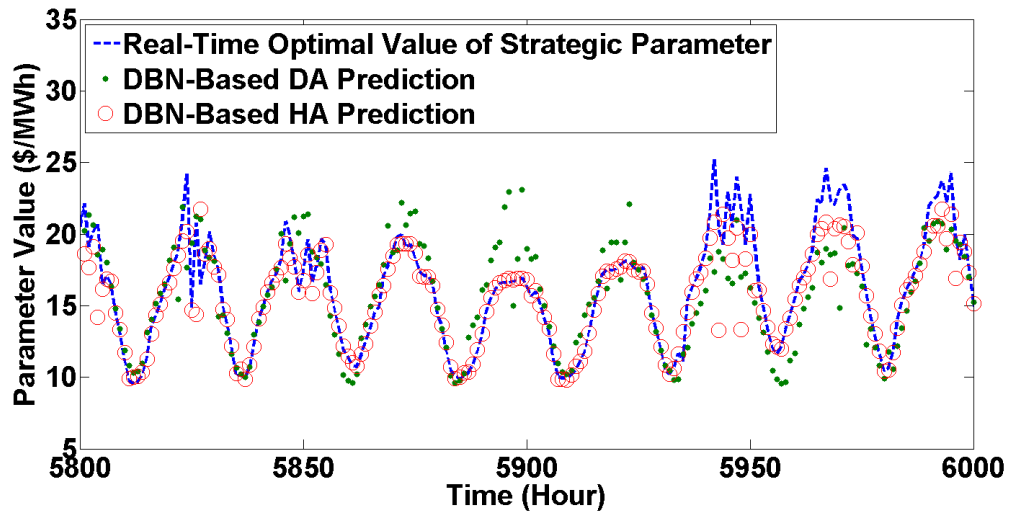


Figure 2.13: DBN-based prediction of optimal action (IEEE 9-bus system)

Case Study IV

The DBN-based decision making scheme is implemented on the IEEE 30-bus system, shown in Fig. 2.14; the data for the system is given in reference [88]. The

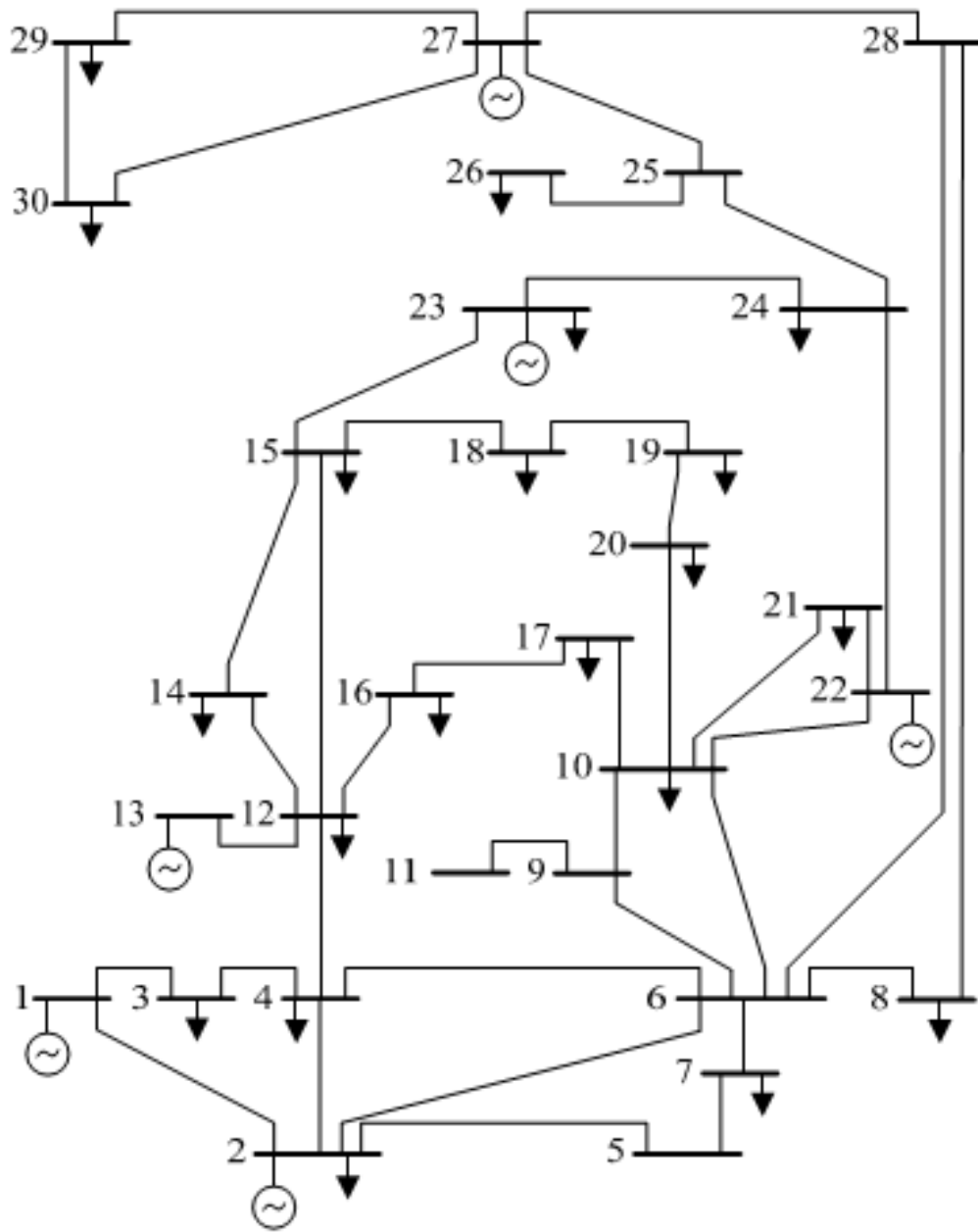


Figure 2.14: Structure of IEEE 30-bus system [88]

cost parameters of the generators (GenCos) are given in Table 2.5, Appendix section of the paper [87]. In Fig. 2.15, and Fig. 2.16 the results of the DBN-based prediction of the strategic parameter for the DA and HA stages are shown, for one of the agents. The MAE of estimation is 10% and 15% for the HA and DA markets, respectively. Note that while the MAE has increased compared to the previous two test cases (due to lower mean value of strategic parameter), the absolute value of the error is in the same range (around \$0.1/MWh to \$0.3/MWh). As expected, the accuracy of the DBN-based decision making procedure in the HA stage has improved compared to the DA stage. The other five agents show similar accuracy in estimating their optimal strategic bidding function.

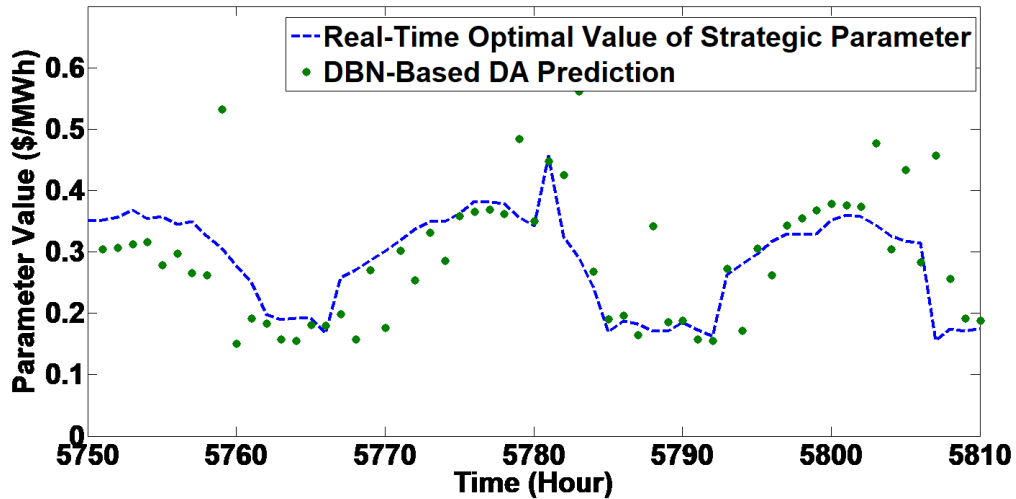


Figure 2.15: DA DBN-based prediction (IEEE 30-bus system)

Comparing DA and HA Bidding Schemes

Since the uncertainty pertaining to load prediction is diminished in HA decision-making, the equilibrium of the HA market is Pareto superior for the GenCos, compared to the DA market. Thus, the GenCos can make additional profit by

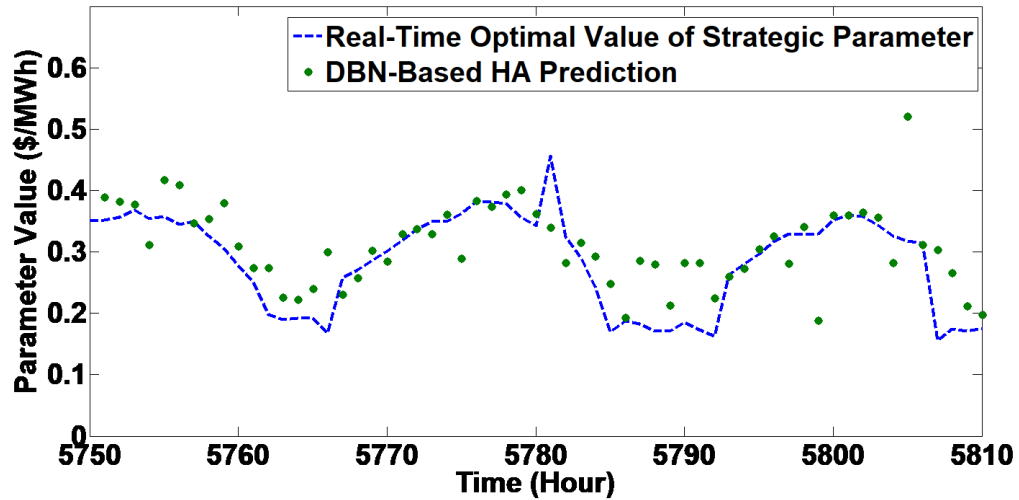


Figure 2.16: HA DBN-based prediction (IEEE 30-bus system)

modifying their DA bidding functions on the HA stage (as they move closer to real-time dispatching). We have compared the profit levels of the GenCo agents in case studies I and III for the DA and DA+HA markets. In the 5-agent system of case study I, an average annual profit level growth of \$90,000 is observed for each agent in the DA+HA market, compared to the DA market.

The results of the simulation in the fourth case study (IEEE 30-bus system) show that introducing the HA stage into the market leads to more stable and less volatile prices, as depicted in Fig. 2.17. Also, the HA stage reduces the volatility of the profit streams of the GenCos. Compared to the single-stage market (i.e., DA only), the mean total profit of the agents for the multistage case (DA+HA) has increased from \$8,800 to \$10,000 in a period of 60 hours. Hence, a multistage procedure is capable of decreasing the risk and improving the stability of the energy market.

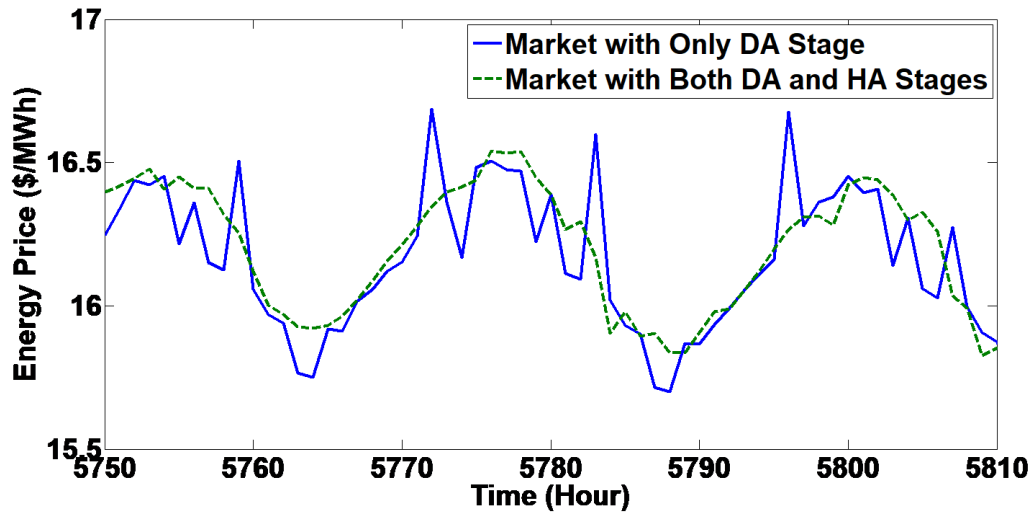


Figure 2.17: Energy prices in single-stage and multistage energy markets

Market Power Analysis

As the number of competing GenCos grow (keeping the total generation capacity fixed), the average share of each GenCo (i.e., market concentration, which is measured by the Hirschman-Herfindahl Index (HHI)) falls [21]. In our study, the HHI value for the 5-agent system is 0.2 while it drops to 0.072 when the number of GenCos increases to 15. On the other hand, the average value of the optimal strategic parameter decreases from \$1.886/MWh, to \$0.835/MWh, as the number of GenCos grow from 5 to 15; this indicates a drop in each GenCo's incentive to exercise market power. In Fig. 2.18, energy prices of the two systems (5-agent and 15-agent) are compared. In addition to an increase in average price in the 5-agent system (\$32.95/MWh compared to \$16.44/MWh for the 15-agent system), the standard deviation of the energy price has also grown (\$2.37/MWh, compared to \$1.24/MWh for the 15-agent system), suggesting higher price volatility for the system with lower number of GenCos. Thus, the model confirms the expected drop in market power exercise as the number of GenCos grow. Also, in both systems, the average correlation level of electrical demand

and the optimal strategic variable is high and almost the same (0.729 in the 15-agent system, and 0.765 in the 5-agent model). The scatter diagram of optimal strategic parameter and electrical demand is shown in Fig. 2.19 for one of the GenCos in the IEEE 30-bus system. As expected, an increase in electrical demand results in excessive market power exercise by GenCos.

The agent-based model shows two sources of volatility in the energy market: the errors in load forecasting, and the low number of GenCo agents. While the former is caused by limitation of forecasting tools in containing the uncertainty of the system (as shown in comparing single-stage and multistage markets), the latter corresponds to direct market power exercise by dominant firms in the market.

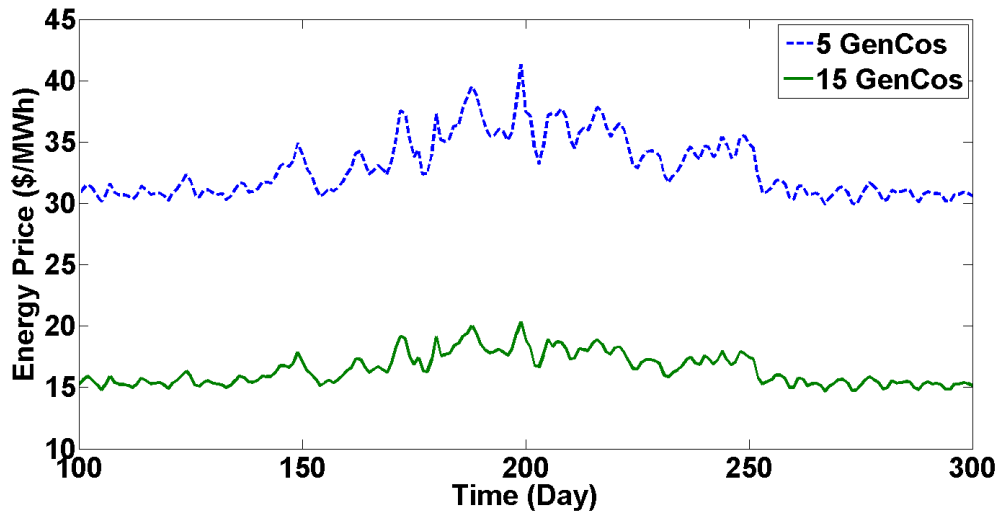


Figure 2.18: Comparing energy prices in systems with 5 and 15 agents

Conclusion

In this paper, an agent-based optimal decision making tool is designed using dynamic Bayesian networks. Employing sparse Bayesian learning, each agent trains its private belief system to predict the optimal course of action to be taken in future

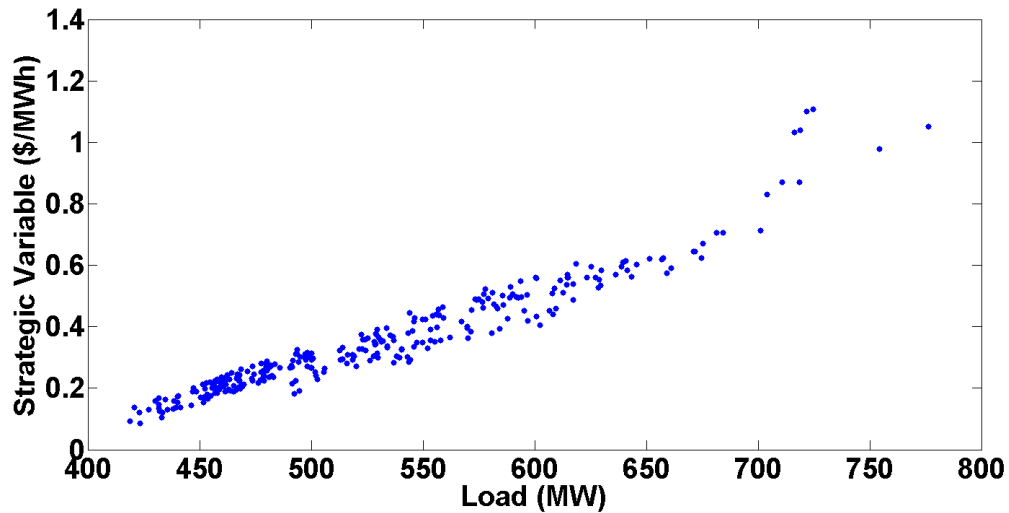


Figure 2.19: Sensitivity of an agent's market power to inelastic electrical demand level

rounds of the market. This distributed decision making model is tested in MATLAB on markets with high and low share concentrations (5 and 15 GenCos, respectively) and on two distinct time scales (HA/DA). Also, the model was tested on two IEEE benchmarks (9-bus and 30-bus systems). Numerical results show that, by using the proposed decision making model, the agents are able to predict the market equilibrium in advance, with acceptable errors. Thus, based on the proposed probabilistic model, the multiagent system approaches a Nash equilibrium through distributed decision-making under incomplete information. The DBN-based belief system can be expanded easily to model more complex decision-making situations.

Appendix: GenCo Cost Data

Table 2.2: Cost Function Parameters for Case Study I

Agent	$a_i(\$/MWh)$	$b_i(\$/MWh^2)$	$P_{max}^i(MW)$
GenCo1	10	0.25	216
GenCo2	16	0.19	193
GenCo3	20	0.1	224
GenCo4	6	0.15	211
GenCo5	22	0.05	206

Table 2.3: Cost Function Parameters for Case Study II

Agent	$a_i(\$/MWh)$	$b_i(\$/MWh^2)$	$P_{max}^i(MW)$
GenCo1	10	0.25	55
GenCo2	16	0.19	40
GenCo3	20	0.1	40
GenCo4	8	0.15	50
GenCo5	22	0.05	45
GenCo6	18	0.25	60
GenCo7	16	0.2	65
GenCo8	14	0.1	70
GenCo9	11	0.13	75
GenCo10	10	0.09	90
GenCo11	10	0.2	75
GenCo12	12	0.1	80
GenCo13	10	0.1	80
GenCo14	6	0.01	110
GenCo15	7	0.02	100

Table 2.4: Cost Function Parameters for Case Study III

Agent	$a_i(\$/MWh)$	$b_i(\$/MWh^2)$	$P_{max}^i(MW)$
GenCo1	5	0.22	250
GenCo2	1.2	0.17	300
GenCo3	1	0.245	120

Table 2.5: Cost Function Parameters for Case Study IV

Agent	$a_i(\$/MWh)$	$b_i(\$/MWh^2)$	$P_{max}^i(MW)$
GenCo1	15	0.02	80
GenCo2	14.75	0.0175	80
GenCo3	16	0.025	50
GenCo4	14	0.0625	50
GenCo5	16	0.025	30
GenCo5	15.25	0.0083	55

AGENT-BASED MODELING OF RETAIL ELECTRICAL ENERGY MARKETS
WITH DEMAND RESPONSE

Contribution of Authors and Co-Authors

Manuscript in Chapter 3

Author: Kaveh Dehghanpour

Contributions: Developed and tested the agent-based decision model for the retail market and load controllers, and prepared the manuscript.

Co-Author: Hashem Nehrir

Contributions: Supervised the overall flow of the project, and provided important insight on numerical studies and interpretation of the results. Aided in the preparation of the manuscript.

Co-Author: John Sheppard

Contributions: Provided important insight on machine-learning-based techniques and interpretation of results. Aided in the preparation of the manuscript.

Co-Author: Nathan Kelly

Contributions: Collaborated with the author for performing simulations.

Manuscript Information Page

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Abstract

In this paper, we study the behavior of a Day-Ahead (DA) retail electrical energy market with price-based Demand Response (DR) from Air Conditioning (AC) loads through a hierarchical multiagent framework, employing a machine learning approach. At the top level of the hierarchy, a retailer agent buys energy from the DA wholesale market and sells it to the consumers. The goal of the retailer agent is to maximize its profit by setting the optimal retail prices, considering the response of the price-sensitive loads. Upon receiving the retail prices, at the lower level of the hierarchy, the AC agents employ a Q-learning algorithm to optimize their consumption patterns through modifying the temperature set-points of the devices, considering both consumption costs and users' comfort preferences. Since the retailer agent does not have direct access to the AC loads' underlying dynamics and decision process (i.e., incomplete information) the data privacy of the consumers becomes a source of uncertainty in the retailer's decision model. The retailer relies on techniques from the field of machine learning to develop a reliable model of the aggregate behavior of the price-sensitive loads to reduce the uncertainty of the decision-making process. Hence, a multiagent framework based on machine learning enables us to address issues such as interoperability and decision-making under incomplete information in a system that maintains the data privacy of the consumers. We will show that using the proposed model, all the agents are able to optimize their behavior simultaneously. Simulation results show that the proposed approach leads to a reduction in overall power consumption cost as the system converges to its equilibrium. This also coincides with maximization in the retailer's profit. We will also show that the same decision architecture can be used to reduce peak load to defer/avoid distribution system upgrades under high penetration of Photo-Voltaic (PV) power in the distribution

feeder.

Introduction

As the structure of power systems evolves along with the rapidly increasing penetration of variable renewable energy resources into the power grids, new techniques are introduced in the context of smart grids [97] to ensure the safe and optimal operation of the electrical energy systems [168]. In this context, Demand Response (DR) has been introduced to give the consumers the opportunity of participating in power system management and control processes.

DR programs are generally classified into two distinct categories [67]: 1) incentive-based DR programs, in which the system operator provides consumers with monetary incentives in return for various ancillary services, such as frequency and voltage regulation services, direct load control, and emergency DR, and 2) time-based DR programs are price-based procedures, including time-of-use pricing, peak-pricing, and real-time pricing. Time-based DR programs are of particular interest in this paper.

The basic idea in price-based DR is to introduce market mechanisms at the retail level, to which automated load control agents are able to respond. In this way, a level of price-sensitivity can be achieved on the demand side; that is, consumers change their consumption patterns in response to varying prices they receive. As shown in [102], in order to maintain the economic efficiency and viability of the markets in practice, the response of the consumers to energy prices needs to be considered and integrated within the pricing process of the market. To achieve this task, bilevel iterative decision models have been proposed at the electrical distribution level [140] [169]. This implies the need for developing smart metering and bidirectional communication networks between consumers and utility companies. As discussed

in [68], the penetration of advanced metering devices throughout the U.S. increased to 36.3% of all the metering devices by July 2014, compared to 22.9% in 2011, and 8.7% in 2010 [67], which shows a promising trend in implementing DR programs.

In this paper, we present a price-based DR procedure for Day-Ahead (DA) planning and decision-making in retail electrical energy markets using an agent-based framework. While this problem has been addressed in the literature using different tools, such as multi-objective optimization [84], mixed integer linear programming [176], model predictive control [34], particle swarm optimization [115], and gradient-based methods [177], the novelty of this paper lies in the use of an agent-based approach, with agents employing techniques from the field of machine learning to model their environment and optimize their behavior. In this way, we can model and study the behavior of retail energy markets in a realistic context without burdening the examination with oversimplifying assumptions on the state of information of different entities in the system. Also, given that different computational tasks are distributed among agents, the proposed solution will be scalable for practical implementation. More specifically, agent-based modeling is employed in this paper to address the problems of interoperability and data privacy in retail power markets. In this paper, we assume that agents have no information on their peers' private data, which addresses the concerns on privacy protection discussed in [67]. This data privacy leads to incomplete information of agents on their peers' behavior, which in turn, contributes to uncertainty in their decision models. In other words, an agent-based framework in combination with machine learning techniques corresponds to the natural state of decentralized and distributed decision-making structure of the interoperable retail energy markets. Interoperability is defined in [56] as: "the capability of two or more networks, systems, devices, applications, or components to exchange information between them and use the information exchanged." The role

of interoperability in grid modernization and integration of new resources in power systems is discussed in [214]. Noting that two of the most essential properties of agents in a multi-agent setting are *autonomy* and *social capability* (i.e., the ability to exchange data with peers) [216], the connection between multi-agent systems and interoperable systems becomes clear and well-founded. Each component of an interoperable network can be viewed as an autonomous agent that interacts with other components.

Also, employing a multi-agent system approach introduces a certain degree of independency in modeling different decision and control mechanisms in the system. For instance, in a multi-agent setting, the decision problem of the retailer and loads can be decoupled completely, since each of them is being handled by distinct agents. This has enabled us to test and compare different decision and control procedures (as has been done in this paper) without having to re-design the whole model from scratch. More on the merits of agent-based modeling can be found in [210].

As shown in the literature [139], Thermostatically Controlled Loads (TCLs) have a high potential for being candidate appliances to participate in a DR program. Due to their considerable thermal capacity, TCLs, can temporarily deviate from their desired consumption pattern without causing significant discomfort to the consumers. Specifically, in this paper, we consider Air Conditioning (AC) loads as primary agents that participate in the price-based DR program. In this way we can observe the effects of the dynamics of the loads on the market.

In [140], the retail market is formulated as a bi-level decision problem, introducing a two-stage pricing mechanism, through a distributed convex optimization problem. Limiting assumptions have been made to keep the optimization problems convex. Also, it is assumed that the pricing mechanism has access to the complete information on the decision problems of the loads. In [176], the reaction of demand

side to energy prices is modeled as simple elasticity coefficients that appear as constraints in the optimization problem of a profit-oriented utility company. While this generic approach provides valuable insight into the decision-making of a utility company, it does not capture the dynamic behavior of loads in the retail pricing process. Another DR scheme is proposed and solved in [171] considering the uncertainty of wind power and grid energy price. In this work, also, generic models have been considered for loads. Moreover, the DR problem is solved through a central optimization problem with access to all consumers' data. In [136], purchase bidding strategies of an energy coalition with a non-profit aggregator and DR is studied, again, through a bi-level decision problem. The authors have relied on Monte-Carlo simulations and stochastic optimization to account for the price-sensitivity of the loads in decision-making. Since no learning mechanism is adopted to direct the search process, the number of iterations required to solve the problem is very high (in the order of 1000). Another iterative pricing mechanism is introduced in [177] to flatten the load profile through peak reduction. In this paper, the utility company relies on estimated gradient of price sensitive demand along the retail prices. Hence, to guarantee the global optimality and proper convergence of the gradient method the authors have kept the optimization problem convex. In an interesting work, the problem of response of the consumers to retail prices is discussed within a bi-level decision problem [169]. In this paper the authors use an iterative scheme and a simulated-annealing-based price control strategy to perform retail energy pricing. The nonlinear dynamics of the loads are ignored and simplified to keep the decision problem of the loads convex.

In our paper, we propose a distributed decision-making framework for implementing a DR program to address several issues that we believe have been ignored and under-studied in the previous works: 1) we avoid simplifying the load models to

obtain convex decision problems. We will show that even simple nonlinear first-order load models lead to non-convex optimization problems on the retailer-side, 2) we keep the decision problem of consumers as simple as possible for ease of implementation, 3) we address the effect of uncertainty in the retailer's decision model resulting from incomplete knowledge about the behavior of the price-sensitive loads and their private settings. It is also critical to investigate how different forecasting tools can be incorporated in the decision model of the retailer to limit the uncertainty of the problem, 4) we study how variations in users' preferences in terms of cost-sensitivity affect the equilibrium of the market.

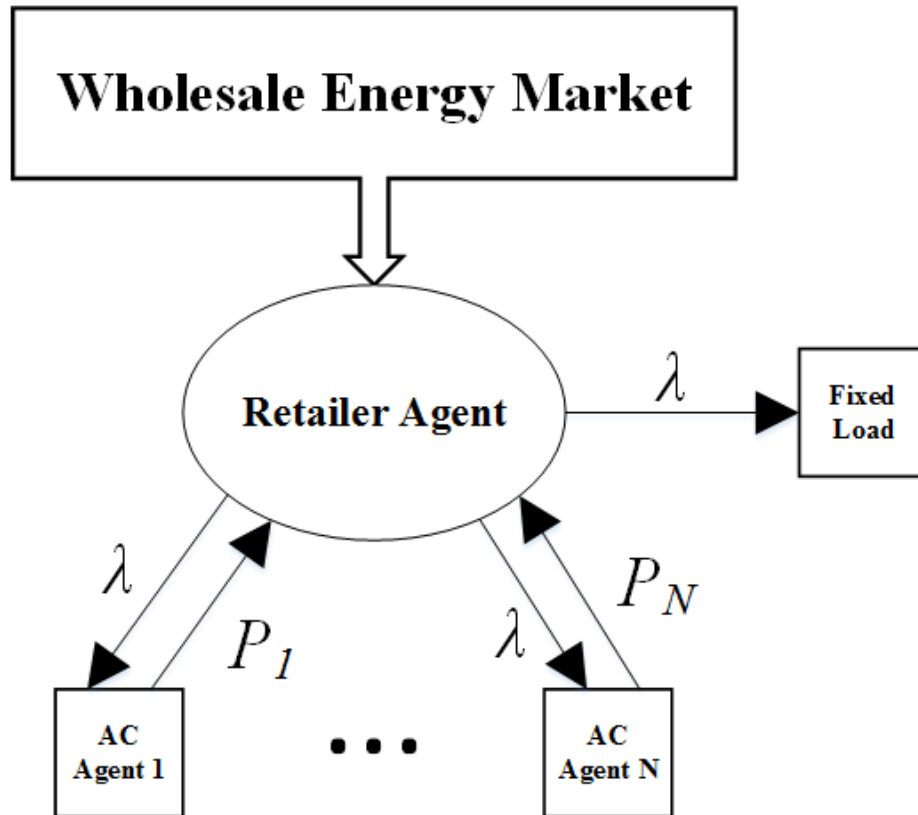


Figure 3.1: The overall architecture of the agent-based model

The proposed hierarchical agent-based framework in this work consists of two

levels, as shown in Fig. 3.1. At the top level, a retailer agent buys energy on the wholesale market and sells it to the consumers, consisting of both fixed and price-sensitive loads. Hence, the retailer can be viewed as a load aggregator and power supplier. The primary objective of the retailer is to maximize its profit from sales of energy. For that purpose, the retailer develops a model of the aggregate response of price-sensitive loads to retail prices. This model is basically a forecasting tool that is learned through interaction with consumers. We consider two possibilities at this stage: a first case in which the retailer employs a linear model, and a second case, for which the retailer uses a nonlinear model in the form of an Artificial Neural Network (ANN) to approximate the aggregate response of the price-sensitive loads. While the linear model is learned using multiple linear regression and QR decomposition [109], the ANN is parameterized via Bayesian Regularized Back Propagation (BRBP) [124]. Using the distinct learned models (i.e., load forecasting tools), the retailer formulates the DA profit maximization problem, which is solved using Particle Swarm Optimization (PSO) [184]. One objective of this paper is to compare the performances of the two modeling approaches. In other words, we will investigate the efficiency of a linear model versus a non-linear model and their effects on the revenue stream of the retailer.

At the lower level of the hierarchy, the AC agents optimize their consumption patterns independently using their local controllers, by setting proper temperature set-points after receiving the retail prices from the retailer, considering both the cost of consumption and the consumers' comfort levels along with the predicted ambient temperature. The consumers have the freedom to determine the trade-off between increasing cost reduction and reducing deviation from comfort zone, through private settings in their decision model. This problem is formulated as a Markov Decision Process (MDP) [193] and solved via Q-learning [193]. Upon calculating their DA

expected consumption profiles, the AC agents send this information as feedback signals to the retailer agent. At this level, we define two case studies: *mild DR* and *active DR*. For the case of mild DR, the population of AC agents shows less sensitivity to retail prices. In *active DR*, however, the portion of consumers that actively seek to cut their consumption costs (at the expense of higher deviations in temperature set-points) dominate the population of the AC agents. These two case studies help us understand the behavior of the retail market as the level of the price-sensitivity of the demand-side participants in the market changes.

The proposed agent-based model is a bi-level sequential decision-making process: the retailer updates its model of the consumers, and revises the retail prices based on the newly received feedback data on aggregate AC consumption levels. On the other end, the AC agents revise their consumption pattern based on the newly received retail prices. This sequential decision-making process relies on the existence of a bidirectional communication network and local decision-making algorithms. As will be demonstrated, using this method, the system converges to its equilibrium. Also, it will be shown that the approach of the system to its equilibrium coincides with a reduction in total consumption cost and magnitude, which shows a promising ground for practical implementation of the algorithm. On the retailer side, the approach of the model to equilibrium coincides with profit maximization.

While our proposed pricing scheme leads to reduction of overall consumption level, it can also lead to creation of minor secondary peaks at later hours of the day, as is shown in Section V. The minor secondary peak could lead to congestion and overloading of the distribution system in the presence of Photo-Voltaic (PV) power in the system. We will show that in addition to profit maximization, the same retail pricing mechanism can be applied by the aggregator to reduce the peak load and mitigate the problem of congestion, as a secondary objective, in high PV penetration

scenarios, in order to avoid/defer distribution system upgrades. In summary the contributions of the paper are as follows:

- Introducing an agent-based approach based on the concept of “learning” to model the retail energy markets with DR. The performance of different machine learning techniques at the retail level are compared, under different case studies.
- Using an MDP and Q-learning to model the behavior of price-sensitive AC loads, considering the uncertainty of their initial conditions. Monte-Carlo simulation was used to obtain the aggregate response of the population of ACs.
- The problem of uncertainty of the decision-making of the retailer (due to incomplete information on the state of price-sensitive loads) is addressed using machine learning techniques to design load forecasting tools.
- The effects of variations in consumers’ private settings and preferences on the equilibrium of the market are addressed.

The rest of this paper is organized as follows: in Sections II, III, and IV the basic functionality of the agent-based framework at the two levels of the hierarchy is described. In Section V, the numerical results are shown and discussed. The main conclusions are presented in Section VI.

AC Agents’ Decision Problem

In this section the functionality of the AC agents in the market will be discussed, and their overall decision-making problem will be explained. The decision problem of each AC load is solved by the individual controller of that load using consumer’s private settings. The market operation is on an hour-by-hour basis.

A heterogeneous population of price-sensitive AC loads is participating in the retail market. The AC agents are in charge of controlling the AC loads by determining optimal DA temperature set-points, based on the forecasted DA ambient temperature and estimated initial states. When determining the temperature set-points, AC agents need to consider three issues: the dynamics of the AC loads, the total cost of energy, and the consumers' comfort level. Note that the DA hourly retail prices act as constant inputs to the loads' decision problems.

The dynamics of TCLs, including ACs, can be described by a non-linear first order system of differential equations as shown in [18]. Using the load dynamics, the DA temperature set-points, and forecasted DA ambient temperature vector, the AC agent is able to estimate the level of consumed power for different hours of the next day. We assume that the temperature forecasting is performed by a Numerical Weather Prediction (NWP) unit, and the predicted set-point values are treated as given inputs in the ACs decision-making units. Note that the dynamics of the load is a source of uncertainty for the problem, since the initial room temperature and thermostat status are not known, *a priori*, by the agents. The dynamics of a single AC is shown in (3.1).

$$\begin{aligned} \frac{dT}{dt} &= \frac{1}{RC}(T_{am} - T(t) - P_N \cdot R \cdot m(t)), \\ m(t) &= \begin{cases} m(t) = 1, & \text{if } T > T_{set} + \frac{\delta}{2} \\ m(t) = 0, & \text{if } T < T_{set} - \frac{\delta}{2} \\ m(t) = m(t-1), & \text{otherwise.} \end{cases} \end{aligned} \quad (3.1)$$

where, parameters R , C , T , T_{am} , and P_N denote room/house thermal resistance, thermal capacitance, inside temperature, ambient temperature, and nominal AC cooling power, respectively. The variable $m(t)$ is a binary variable that represents the

Table 3.1: Average Values of AC Load Parameters

Parameter	Value
R	2 C/kW
C	10 kWh/ C
P_N	14 kW
δ	1 C
T_{des}	19 C
η	2.5

ON/OFF thermostat status, with δ being the operational dead-band of the device. The nominal electrical power of the AC load (P_e) is obtained using :

$$P_e = \frac{P_N}{\eta} \quad (3.2)$$

where, η is the load efficiency. The *average* values of load parameters, selected according to [18], are given in Table 3.1.

To perform the decision-making, the problem is formulated as an MDP (Fig. 3.2). At each state the agent can select from a set of available actions. The selected action then leads the agent to another state, based on a state transition function. Also, each state transition results in a penalty value for the agent, according to the MDP's penalty function. The goal of the agent is to minimize its aggregate penalty by finding the optimal action at each state (note that each AC agent is equipped with its own private MDP).

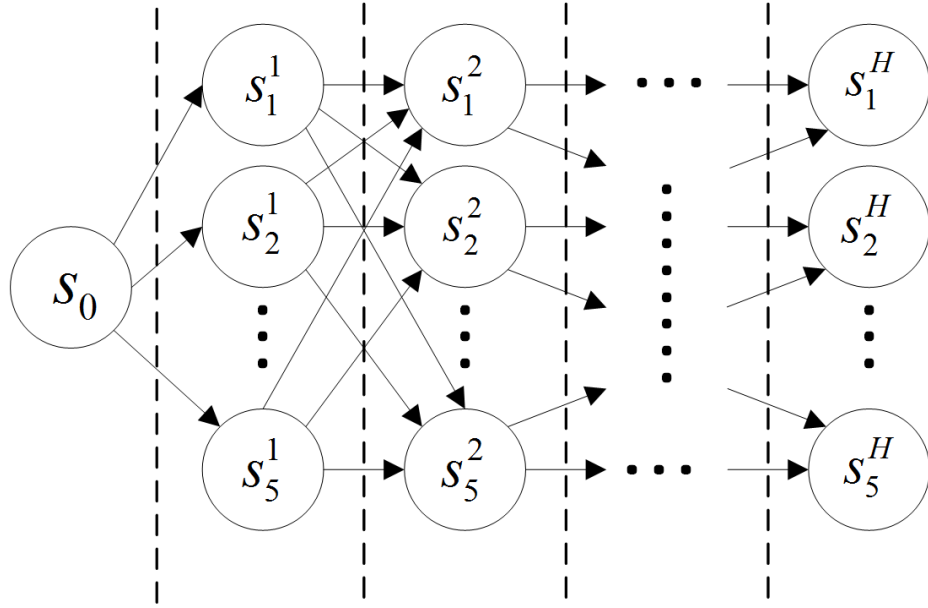


Figure 3.2: Proposed MDP for AC level decision-making

The immediate penalty within the proposed MDP is defined by two parameters: the estimated DA consumed power, which is obtained by the load dynamic model, and the violation of consumer's comfort level, which is defined by the absolute value of temperature set-point deviation from the consumer's desired temperature. Hence, the immediate penalty function consists of two competing terms: one objective is to minimize total energy costs, and the other is to stay within the consumer's comfort zone as often as possible. The consumer has the freedom of balancing these two objectives by assigning weights to them. The states of the MDP specify the allowed discretized values of deviation of temperature set-point from the desired temperature at each hour of the next day.

Five states are defined for each hour of the day, with each state corresponding to certain degrees of deviation in the temperature set-point (T_{set}) from the desired temperature (T_{des}) at each specific hour. The average value of T_{des} over the population of AC loads is given in Table 3.1. The deviation values, in Celsius, are selected from

the set $\{+2, +1, 0, -1, -2\}$, corresponding to states s_1 through s_5 , respectively. For instance, s_2^j implies +1 C deviation in temperature set-point of the AC from the desired temperature at the j^{th} hour of the day, with j changing from 1 to $H = 24$ (with H denoting the planning period). The immediate penalty (π) for an action at the $(j - 1)^{\text{th}}$ hour is calculated as follows:

$$\pi^j = \frac{|T_{set}^j - T_{des}|}{N_1} w_1 + \frac{p^j \lambda^j}{N_2} w_2. \quad (3.3)$$

The first term in (3.3) (i.e., $\frac{|T_{set}^j - T_{des}|}{N_1} w_1$) penalizes deviations from the desired temperature level at the j^{th} hour (with N_1 as normalizer). The second term (i.e., $\frac{p^j \lambda^j}{N_2} w_2$) penalizes the total cost of consumed electrical energy for the j^{th} hour of the day (with p^j , λ^j and N_2 denoting total energy consumption at the j^{th} hour, retail price at the j^{th} hour, and a normalizer term, respectively). Here, N_1 and N_2 are equal to the maximum temperature set-point deviation and maximum consumption cost, respectively. Hence, the first term serves as a measure of the consumer's comfort level, while the second term acts as a measure of the tendency of the consumer to cut energy costs. Different consumers have different preferences on balancing their energy costs and comfort levels, which is modeled as the two weights in the penalty function, w_1 , and w_2 , with: $w_1, w_2 \in [0, 1]$, $w_1 + w_2 = 1$.

Q-learning [193], which is a type of model-free reinforcement learning algorithm, is used to obtain the optimal sequence of temperature set-points for the device. Using Q-learning, an agent can find the optimal course of action without having full knowledge of transition and penalty functions of the MDP. The basic idea of Q-learning is to assign a Q-value to each state-action pair at time t , i.e., $Q(s_t, a_t)$, and update it at each encounter, in a way to reinforce good behavior. The Q-values correspond to the long-term “worth” of state-action pairs. Hence, each AC agent

develops a private look-up table that contains the Q-values of the state-action pairs of the proposed MDP. The update mechanism for the Q-values in the look-up table is shown below:

$$Q(s_t, a_t) := Q(s_t, a_t) + \alpha_t \cdot (-\pi_t + \gamma \cdot \max_a Q(s_{t+1}, a) - Q(s_t, a_t)) \quad (3.4)$$

where, α_t is a variable learning rate, π_t is the immediate penalty (obtained according to (3.3)), and γ is a discount factor. In order to take uncertainties of load dynamics into account, (i.e., uncertain initial room temperature and initial thermostat state) the learning process will be repeated for a high number of episodes with different initial conditions. Consequently, we can ensure that the ACs will have an expected desirable behavior under different real-time scenarios.

Note that the coefficients w_1 , and w_2 in (3.3) are “user-defined”, for each AC agent. This means that based on private preferences, the consumers are able to modify the rate of “price-sensitivity” of their appliance, even “turning off” the cost-sensitive module altogether, by setting $w_2 = 0$. Hence, based on the distribution of w_1 , and w_2 in the population of AC agents, two types of DR programs are defined. We will investigate and compare the maximum profit level of the retailer under these two programs.

1. Mild DR: In this case, the value of w_1 is selected according to a uniform distribution over the interval (i.e., $w_1 \sim U[0, 1]$). This mean that the number of AC agents that value comfort level over savings in monetary costs are roughly the same as the number of AC agents that actively seek to reduce consumption costs.
2. Active DR: In this case, w_1 values for the AC agents are selected based on a uniform distribution over the interval (i.e., $w_1 \sim U[0, 0.5]$), which implies

that the AC agents that value consumption cost savings over comfort level constraints dominate the population. An active DR corresponds to increased price-sensitivity of consumers in the retail markets.

Employing Q-learning to address the decision problem of consumers has several advantages that are discussed below:

- Q-learning is model free. Hence, the decision strategy is independent of the agent's knowledge of the AC load model. This implies that the proposed method can be generalized to more complex AC load models. The model-free nature of Q-learning provides the decision-making agents with higher levels of flexibility and controllability over the classical optimization approaches, such as linear programming [13]. While in linear programming we need to linearize the underlying dynamics of the loads to solve the optimization problem, in a model-free approach such as Q-learning, the solution strategy is independent of the properties of the underlying models. Hence, we are able to capture the effects of the non-linearity of the models on the decision problem.
- Another advantage of Q-learning is its simplicity. The whole computational process of the algorithm is based on a look-up table and an update rule (equation (3.4)). The ease of implementation of an algorithm is crucial, specifically at electrical distribution level and for home energy management systems.
- Also, through Q-learning, the uncertainty of the system can be considered in the decision-making process. This is achieved through episodic learning, as explained previously. The update process, (3.4), takes place under different episodes. Each of these episodes represent different scenarios that reflect our incomplete and uncertain knowledge of different variables in the decision model. In this paper episodic learning is performed to account for the uncertainty of

the initial state of the AC devices in real-time (i.e., initial ON/OFF status and initial temperature according to probability distribution functions in [18]).

- Q-learning is a reinforcement learning method. Thus, unlike supervised learning schemes, in Q-learning we do not need to provide the decision-making agents with correct or optimal solution samples beforehand. Through interactions with their environment the agents are able to obtain the optimal course of action to maximize their pay-off level. In this case, provided with a load model, the AC agents are able to track the optimal temperature set-points for given prices at different hours of the day.

Also, other alternative methods were tried instead of Q-learning, such as the value-iteration [193] method and non-linear programming [13] (solved using PSO). However, Q-learning showed better performance in terms of speed of convergence and quality of final results.

Retailer Agent's Decision Problem

The retailer agent (i.e., the aggregator) develops a model based on the feedback signals it receives from the AC agents to approximate the aggregate behavior of price-sensitive loads as a function of the retail price vector composed of hourly prices. Hence, the goal of the retailer is to perform a function approximation procedure. This model is learned and incorporated into the profit maximization problem of the retailer agent. The outcome of the optimization problem is the optimal retail price vector, which is consequently sent to the price-sensitive loads via the communication network. The same decision model and pricing mechanism can be used for peak reduction, with minor changes. We discuss peak shaving (Sections III.C and V.C)

as a secondary objective for the retailer agent, in the presence of PV power in the distribution feeder.

Two distinct modeling approaches on the retailer side are studied and compared in this paper: using a linear model, and a non-linear ANN-based model. Each of these modeling approaches leads to a distinct optimization problem formulation for the retailer. In this section, we also address the problem of solving the profit maximization/peak reduction for each adopted model.

Linear Model

This model represents the aggregate consumed power of the price-sensitive loads at each hour of the day as a linear combination of hourly retail prices, as shown below:

$$\begin{bmatrix} P^1 \\ \vdots \\ P^H \end{bmatrix} = \begin{bmatrix} a_{11} & \dots & a_{1H} \\ \vdots & \ddots & \vdots \\ a_{H1} & \dots & a_{HH} \end{bmatrix} \begin{bmatrix} \lambda^1 \\ \vdots \\ \lambda^H \end{bmatrix} + \begin{bmatrix} P_0^1 \\ \vdots \\ P_0^H \end{bmatrix} \quad (3.5)$$

where P^j and λ^j denote the total consumed energy of the AC loads and the retail energy price at the j^{th} hour of the day, with j changing from 1 to $H = 24$. This model is learned through multiple linear regression, employing QR decomposition. Equivalently, (3.5) can be written as,

$$\mathbf{P} = \mathbf{A}\boldsymbol{\lambda} + \mathbf{P}_0. \quad (3.6)$$

Using (3.6), the retailer agent is able to develop and maximize its total profit to obtain the optimal set of retail prices. The profit maximization problem is formulated as follows:

$$\max_{\lambda^1, \dots, \lambda^H} \sum_{i=1}^H (\lambda^i - \lambda_g^i)(P^i + P_f^i), \quad (3.7)$$

where, λ_g^i , and P_f^i denote the wholesale DA energy price, and fixed power consumption, respectively (all at the i^{th} hour of the next day). Using (3.6), this optimization problem can be written as:

$$\min_{\lambda^1, \dots, \lambda^H} \sum_{i=1}^H -(\lambda^i - \lambda_g^i)(\mathbf{a}_i \cdot \boldsymbol{\lambda} + P_0^i + P_f^i), \quad (3.8)$$

with \mathbf{a}_i being the i^{th} row of matrix \mathbf{A} . Employing algebraic manipulations, (3.8) is transformed into a non-convex constrained quadratic programming problem as follows [13]:

$$\begin{aligned} \min_{\boldsymbol{\lambda}} & -\boldsymbol{\lambda}^T \mathbf{A} \boldsymbol{\lambda} + (\boldsymbol{\lambda}_g^T \mathbf{A} - \mathbf{P}_0^T - \mathbf{P}_f^T) \boldsymbol{\lambda} + (\boldsymbol{\lambda}_g^T \mathbf{P}_0 + \boldsymbol{\lambda}_g^T \mathbf{p}_f), \\ \text{s.t.} & \begin{cases} \boldsymbol{\lambda}_{min} \preceq \boldsymbol{\lambda} \preceq \boldsymbol{\lambda}_{max} \\ \frac{1}{H} \sum_{i=1}^H \lambda^i = \frac{1}{H} \sum_{i=1}^H \lambda_g^i. \end{cases} \end{aligned} \quad (3.9)$$

where “ \preceq ” denotes element-wise “ \leq ” operator for vectors. The constraints in (3.9) are designed to ensure two properties: the retail prices remain bounded, and the average retail price would be constant (in this case equal to average wholesale prices). These properties can be viewed as regulatory requirements or even mutual agreements among the retailer and its customers, to keep the prices “fair”. The retailer has a short-term monopoly over the consumers due to long-term contracts with them. Therefore, the solution to the optimization would always be $\boldsymbol{\lambda} = \boldsymbol{\lambda}_{max}$, without the introduced constraint on the average retail prices, given in (3.9). Also, under fixed and frozen retail energy pricing, the fixed retail prices reflect the long term average wholesale electricity prices [2]. Hence, we believe the constraints in the optimization problem (3.9) are necessary to connect the wholesale and retail market models, even under time-varying retail tariffs.

The output of (3.9) gives us the optimal retail prices for each hour of the next day. These prices are generated at each iteration and sent to the consumers. Upon receiving the power consumption feedback signals from the AC agents, model (3.6) is updated and (3.9) is solved again to update the prices.

Nonlinear ANN-based Model

Unlike a linear model, an ANN is able to capture the non-linearity of the loads' aggregate behavior. To implement an ANN-based model of the collective behavior of AC agents, the retailer agent employs a three-layer feedforward structure of artificial neurons [178]. The input and output layers consist of **24** neurons each. The hidden layer consists of **25** neurons, chosen using cross validation. BRBP is adopted for learning the weights of the connections within the network. BRBP is computationally burdensome; however, it produced superior results for this application (i.e., higher predictive capabilities), compared to other learning approaches. The functionality and advantages of BRBP are discussed in [124], and [123].

Basically, after training, the ANN will be able to map the retail price vector to the aggregate power consumption vector of the AC agents. This nonlinear mapping can be shown as follows:

$$\mathbf{P} = \mathit{Net}(\boldsymbol{\lambda}). \quad (3.10)$$

Then the retailer's profit maximization problem (with the same set of constraints as (3.9)) can be formulated as,

$$\begin{aligned} & \min_{\lambda_1, \dots, \lambda_H} -(\mathit{Net}(\boldsymbol{\lambda}) + \mathbf{P}_f)^T(\boldsymbol{\lambda} - \boldsymbol{\lambda}_g), \\ & \text{s.t.} \begin{cases} \boldsymbol{\lambda}_{\min} \preceq \boldsymbol{\lambda} \preceq \boldsymbol{\lambda}_{\max} \\ \frac{1}{H} \sum_{i=1}^H \lambda^i = \frac{1}{H} \sum_{i=1}^H \lambda_g^i. \end{cases} \end{aligned} \quad (3.11)$$

Since an ANN acts as a “black box” within the objective function, solving (3.11) directly is not easy (in contrast to (3.9), which was based on a linear model). However, by defining a “fitness” function for (3.11), population-based algorithms can be applied to solve it. In this paper we have chosen PSO as a solver to (3.11). Also, to provide a fair comparison of the linear and ANN-based models, PSO has been used to solve (3.9), as well.

Peak Reduction

The energy pricing mechanism employed by the load aggregator agent for profit maximization can also be used to reduce peak value of the load to avoid/defer distribution system upgrades. The basic difference with problems (3.9) and (3.11) is that the objective function of the peak reduction problem would be the maximum load value, instead of profit level. Hence, the energy pricing mechanism is performed as follows:

$$\begin{aligned} \min_{\lambda_1, \dots, \lambda_H} \left(\max_{i=\{1, \dots, H\}} (Net(\boldsymbol{\lambda} + \mathbf{P}_f - \mathbf{P}_R)) \right), \\ \text{s.t.} \begin{cases} \boldsymbol{\lambda}_{min} \preceq \boldsymbol{\lambda} \preceq \boldsymbol{\lambda}_{max} \\ \frac{1}{H} \sum_{i=1}^H \lambda^i = \frac{1}{H} \sum_{i=1}^H \lambda_g^i. \end{cases} \end{aligned} \quad (3.12)$$

where, \mathbf{P}_R denotes the forecasted renewable power values for the given decision window. As we will show in the result section, the problem of peak reduction and secondary peaks in presence of solar power is of critical importance at distribution level. Hence, we have solved (3.12) for a distribution system with high penetration of PV power.

Solution Strategy

In order to incorporate the constraints of the optimization problems into the PSO, different heuristics have been introduced in the literature [95]. Here, to deal with the equality constraint, we have added a penalty term to the fitness function to penalize deviations of the particles from the feasible region. To handle the inequality constraints, at each iteration, the elements of retail price vector ($\boldsymbol{\lambda}$) that violate the maximum and minimum price limits are removed and replaced with the maximum or minimum price values, depending on the constraint boundary that was crossed. Hence, the augmented fitness function is as follows,

$$\mathbf{Fitness}(\boldsymbol{\lambda}) = \mathbf{Profit}(\boldsymbol{\lambda}) - \gamma \left| \frac{1}{H} \sum_{i=1}^H \lambda^i - \frac{1}{H} \sum_{i=1}^H \lambda_g^i \right|, \quad (3.13)$$

where, γ is the penalty coefficient which is treated as another tunable parameter in the model. The profit function, $\mathbf{Profit}(\boldsymbol{\lambda})$, is obtained for the linear and ANN-based models according to the objective functions of (3.9), and (3.11), respectively. For the problem of peak reduction, we simply replace $\mathbf{Profit}(\boldsymbol{\lambda})$ with $\mathbf{Peak}(\boldsymbol{\lambda})$ in (3.13). $\mathbf{Peak}(\boldsymbol{\lambda})$ denotes the peak load level for retail price $\boldsymbol{\lambda}$, which is obtained using the objective function of optimization problem (3.12).

Considering the fitness function given by (3.13), the base dynamics of the PSO algorithm is according to the following update rules (denoting the positions of the i^{th} particle by \mathbf{X}_i and its speed by \mathbf{V}_i):

$$\mathbf{V}_i^{k+1} = \omega_k \mathbf{V}_i^k + c_1 r_1 (\mathbf{pBest}_i^k - \mathbf{X}_i^k) + c_2 r_2 (\mathbf{gBest}^k - \mathbf{X}_i^k)$$

$$\mathbf{X}_i^{k+1} = \mathbf{X}_i^k + \mathbf{V}_i^{k+1}$$

$$\omega_k = \omega_{max} - \frac{\omega_{max} - \omega_{min}}{k_{max}} k, \quad (3.14)$$

with ω_k acting as a weight parameter (ω_{max} and ω_{min} represent the maximum and minimum values of the weight), c_1 and c_2 used as tunable coefficients, r_1 and r_2 being uniformly generated random numbers from the $[0,1]$ interval, $pBest_i^k$ and $gBest^k$ representing the personal and global best solutions, and k_{max} denoting the maximum number of iterations of the algorithm.

Parameter tuning for (3.14) is performed based on numerical tests on the model. The values of the parameters that showed the best performances are as follows: $c_1 = 0.1$, $c_2 = 7$, $\omega_{max} = 0.9$, $\omega_{min} = 0.1$, and $k_{max} = 15000$. Also, the size of the swarm of particles is selected to be 50. The large number of the particles is due to the relatively high dimensionality of the decision variable (i.e., $\mathbf{X} \in \mathcal{R}^{24}$).

Putting The Pieces Together

Fig. 3.3 shows a flow-diagram of the step-by-step iterative process of the model on the retailer side and the consumer (AC) side, referring to the equations used at each step. The algorithm needs a number of iterations to converge. At each iteration, the retailer agent updates the linear model or the ANN, and calculates the optimal retail prices based on the learned model. These prices are sent to the AC agents that obtain their optimal consumption patterns using Q-learning. Then, the AC agents send back their expected consumption levels to the retailer, to be used for the next iteration. The minimum number of iterations needed for the convergence of the system depends on the sample complexity of the model that the retailer employs [17]. Basically,

sample complexity determines the required number of samples (i.e., iterations) to learn and develop reliable models and avoid overfitting. At each iteration, using the learned model, the retailer has the opportunity to predict the aggregate response of the AC agents to the obtained optimal price vector. The prediction Mean Absolute Error (MAE) is used as a measure of deciding whether overfitting occurs or not. As lower values of MAE are achieved through iterations, the learned model becomes more reliable for decision-making. Note that the prediction MAE is a measure of the uncertainty of the decision model of the retailer agent, caused by incomplete information on private control processes and individual settings of AC agents (due to data privacy).

Numerical Experiments and Results

The proposed method is tested on a sample distribution feeder with one retailer agent and 200 AC agents. The parameters of the AC agents are selected according to log-normal distribution functions used in [18]. The weight values \mathbf{w}_1 , and \mathbf{w}_2 are determined using uniform random distribution functions to represent the two different types of DR programs (mild and active DR) discussed in Section II. Also, the predicted DA ambient temperature for a summer-day, adopted from [217], is shown in Fig. 3.4. The daily fixed load data for the feeder is based on [152], and [83]. The peak value of the fixed load profile is 1.4 MW. On the other hand, the peak value of the aggregate AC consumption level without DR is 0.8 MW, which is around 35% of the total load peak value. The DA energy prices are chosen from real DA price data of the PJM market [165]. Evaluation of the performance of the AC agents and the retailer agents is discussed in this section.

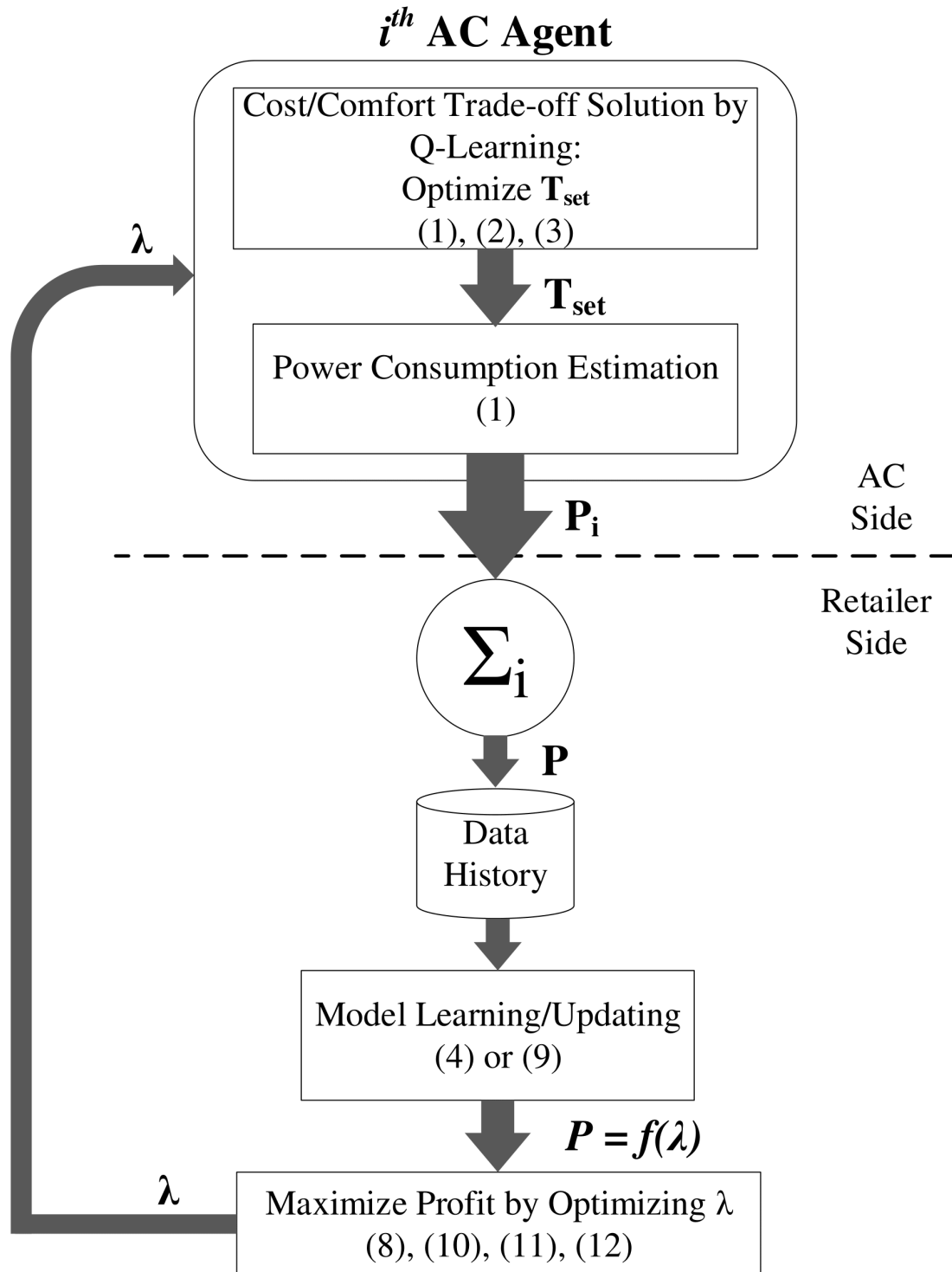


Figure 3.3: Flow-diagram of the agent-based model at each iteration

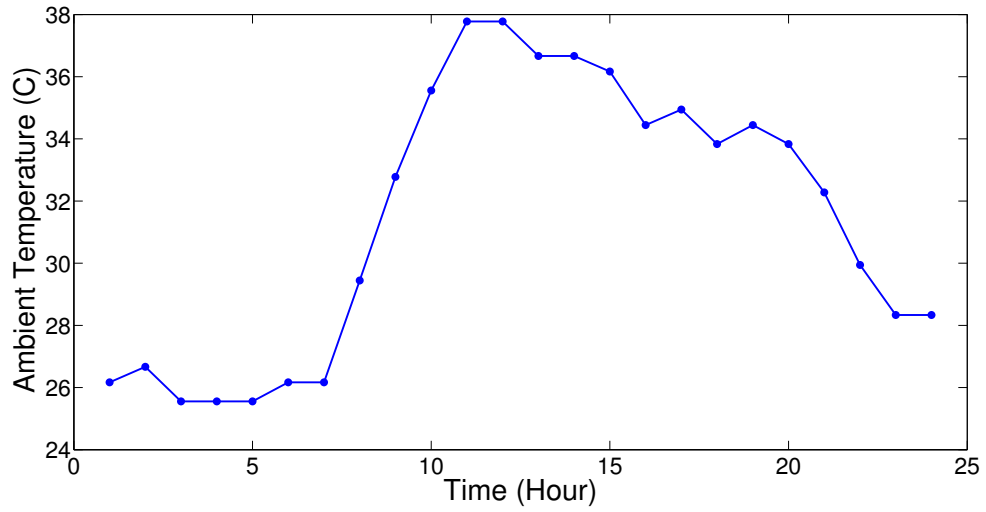


Figure 3.4: Forecasted ambient temperature

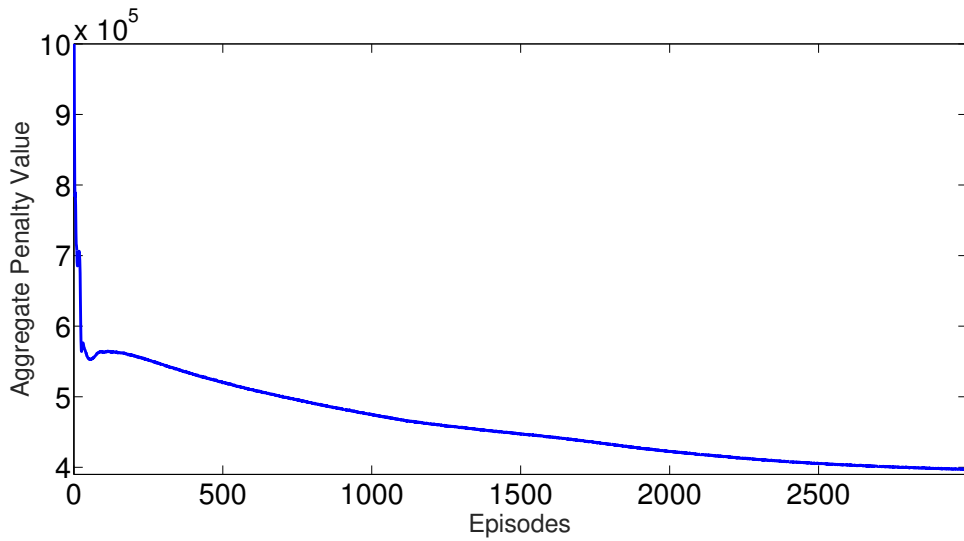


Figure 3.5: Aggregate accumulated penalty of the AC agent using Q-learning

AC Agents' Performance

To verify the performance of the AC agents, the total accumulated penalty values of all the 200 agents over the episodes is shown in Fig. 3.5 for a certain retail price vector. As can be seen, the penalty curve is decreasing in episodes, which implies that the AC agents are able to reduce the overall cost using Q-learning. Also, in Fig. 3.6 and 3.7 the final DA average temperature set-point distribution of all the devices is shown for the mild and active DR programs, respectively. By comparing Fig. 3.6 and Fig. 3.7, we observe that in an active DR program, the average temperature set-points tend to show higher deviations from the case without DR. Also, comparing the two cases of mild and active DR we observe a higher standard deviation in the temperature set-point profile for the latter. This implies that as price-sensitivity increases on the consumer side, the retailer faces a higher level of uncertainty (i.e., it would be more difficult to predict the response of the AC agents to prices).

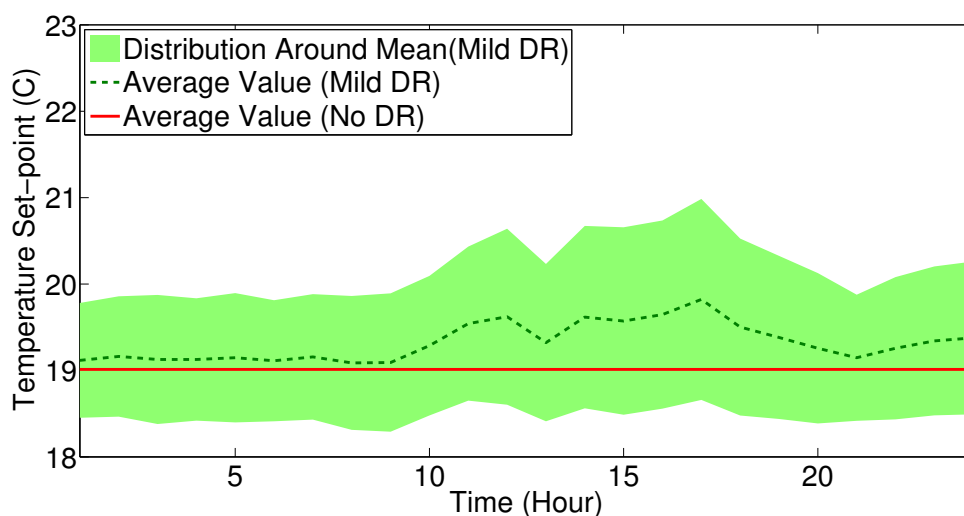


Figure 3.6: Temperature set-point distribution over time for the case of mild DR

As observed in Fig. 3.6 and 3.7, the AC loads go through a “pre-cooling” period during the first few hours (i.e., average temperature set-point is kept around the

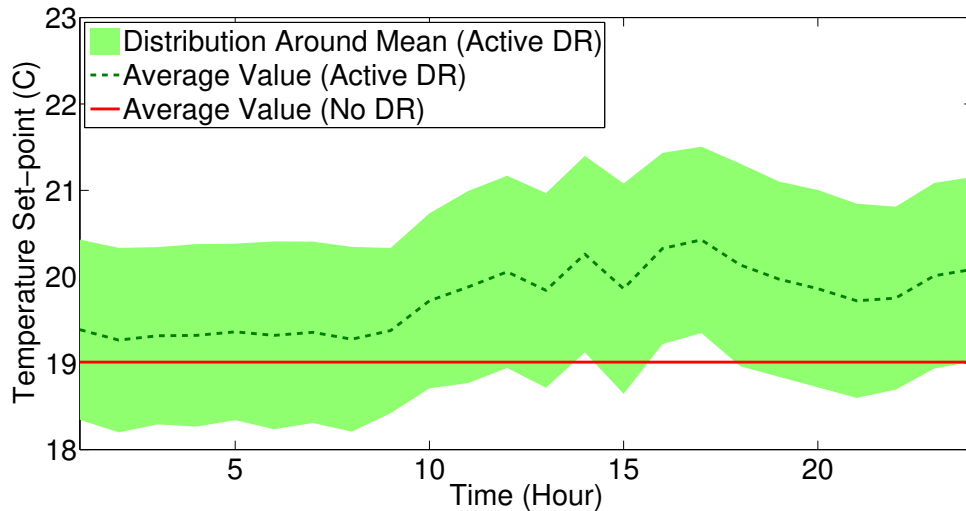


Figure 3.7: Temperature set-point distribution over time for the case of active DR

average desired value) in order to be able to remain deactivated during the hours with higher prices without violating the temperature constraints. In the final few hours of the day, a slight increase in the average temperature set-points is observed, which brings the consumption cost back almost to its initial levels, as shown in Fig. 3.8. The drop and a slight shift in the consumption cost is shown in this figure. The total payment of the AC agents for consuming energy for the day in different scenarios are: \$653 (without DR), \$570.3 (mild DR), and \$512.4 (active DR). Hence, using the case without DR scenario as a base, the reductions in cost of consumption are equal to 12.6%, and 21.5% for mild and active DR cases, respectively. These values have been obtained based on the optimal retail prices received from the retailer, as discussed in the next subsection. Hence, the total payment of the AC agents is equal to the maximum revenue value of the retailer.

The overall DA load profile (consisting of both price-sensitive and fixed electrical demand) is shown in Fig. 3.9. As is demonstrated in this figure, the DR program leads to a decrease in the peak value and shifting of the load to the later hours of the

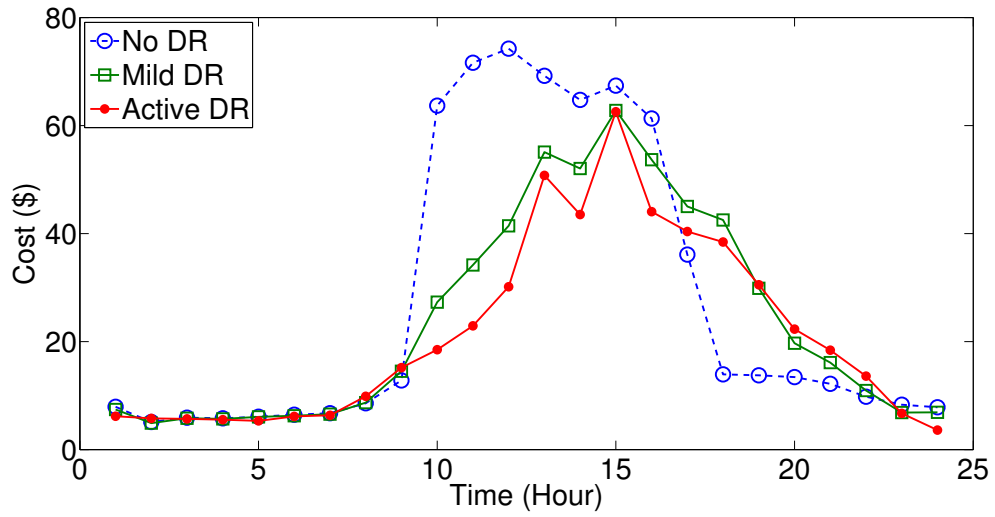


Figure 3.8: Overall cost profile of the AC agents

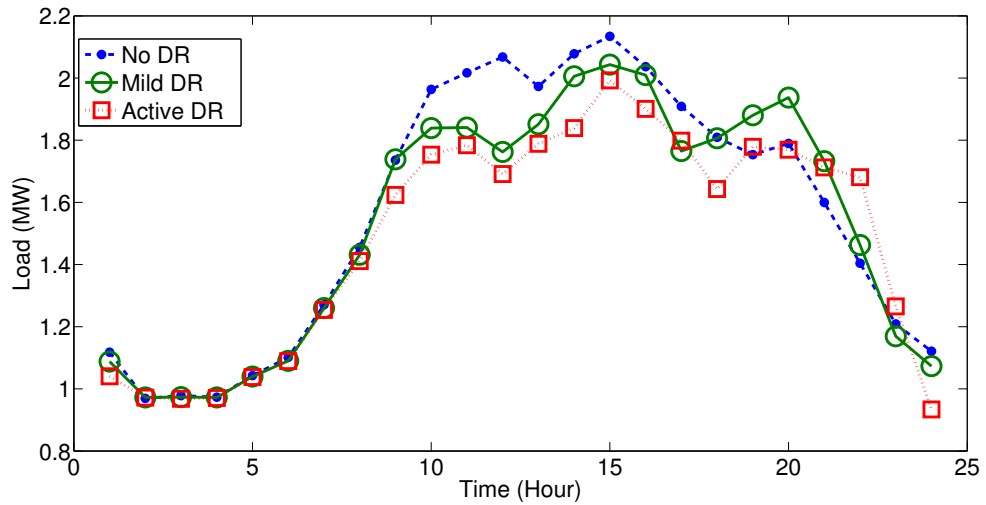


Figure 3.9: DA load profile of the system

day. The peak load drops from 2.134 MW to around 2.084 MW (2.34% decrease). The total reductions in the AC power consumption level compared to the case without DR are equal to 6.03% (mild DR), and 14.67% (active DR). Hence, the AC agents are able to reach considerable consumption cost reductions with relatively low cuts in their consumed power levels. The percentage reduction in cost is approximately between 1.5 to 2 times the percentage reduction in overall consumption of AC loads, up to the point where the load response reaches its maximum level and is saturated.

Retailer Agent's Performance

On the retailer side where the profit maximization problem is solved, the retailer agent's prediction MAE is shown in Fig. 3.10 and 3.11 for the mild and active DR programs, respectively. For the case of mild DR (Fig. 3.10), the MAE of prediction converges to 6.08% (ANN-based model), and 9.95% (linear model). Hence, the long term MAE of the ANN-based model falls below that of the linear model. However, in the short term (iterations 50 to 100) the linear model is able to show similar or even better performance than the ANN. The faster convergence of the linear model implies that we can get to the optimal operation point of the multi-agent system in fewer iterations compared to ANN. For the case of active DR, similar observations can be made. Here, the DA prediction errors are generally higher compared to the mild DR situations. However, as can be seen in Fig. 3.11, the long term prediction MAE of the ANN is 14.66%, which is considerably lower than that of the linear model (27.89%). This suggests that as the behavior of the demand side in response to time-varying retail prices gets more uncertain, a non-linear and more powerful tool such as ANN is able to outperform the linear function approximation approach. Hence, ANN is able to better capture the response of the loads to the prices and reduce the uncertainty in the decision model that is caused by data privacy (i.e., the incomplete information of

the retailer agent on the state of AC loads.) The estimated Probability Distribution

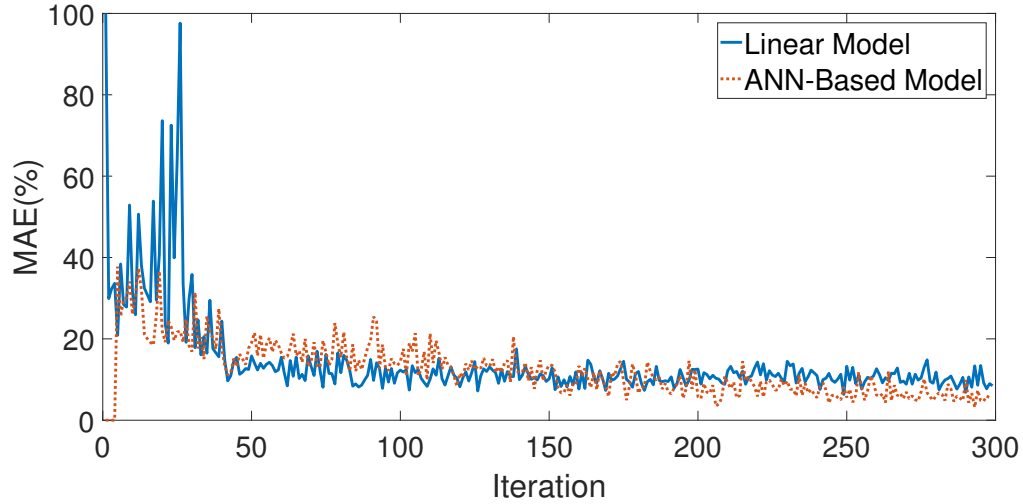


Figure 3.10: Retailer prediction error for the case of mild DR

Functions (PDF) of the prediction MAE of the two models are depicted in Fig. 3.12 and 3.13 for the mild and active cases, respectively. Although the prediction MAE has a symmetric, almost Gaussian shape distribution under the linear model, for the ANN-based model it is skewed. While the mean of the MAE is lower for the ANN (implying superior performance), it has a higher standard deviation (mild DR: 3.67%, active DR: 8.67%) compared to the case of the linear model (mild DR: 1.85%, active DR: 4.71%). Moreover, the standard deviations of the PDFs increase considerably for the case of active DR.

Now the question is whether the enhanced prediction accuracy of the ANN leads to monetary gains for the retailer agent. The profit level of the retailer over the iterations is shown in Fig. 3.14 and 3.15 for the cases of mild and active DR, respectively. As can be seen in the figures, after the initial phase of learning, where the retailer is collecting enough samples to address the problem of overfitting, the profit level of the retailer agent increases and reaches its maximum amount. In the

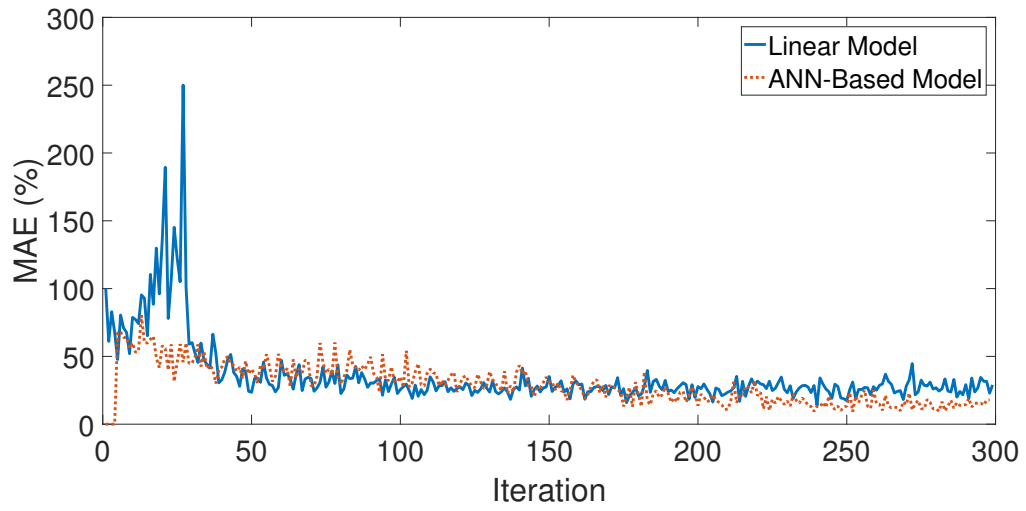


Figure 3.11: Retailer prediction error for the case of active DR

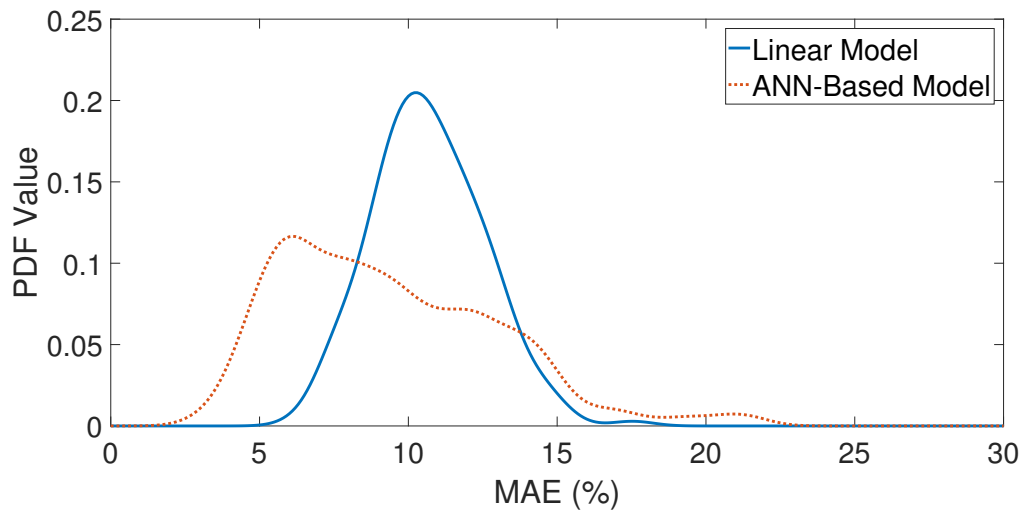


Figure 3.12: The estimated PDF of the retailer's prediction error for the case of mild DR

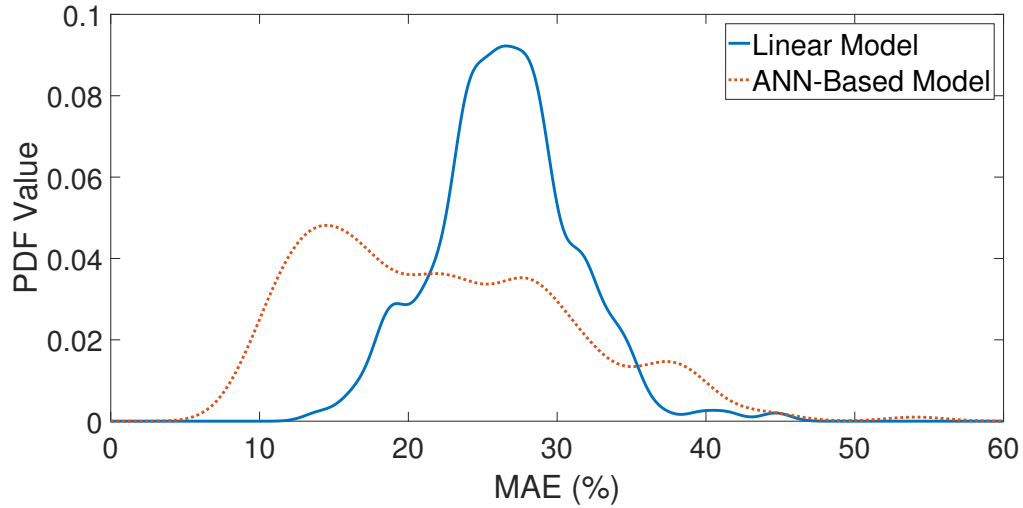


Figure 3.13: The estimated PDF of the retailer's prediction error for the case of active DR

case of mild DR, the total profit of the retailer per day is \$42.4 for the linear model and \$41.3 for the ANN-based model. The mean average difference in the optimal retail price under the two models is around 1%. Hence, for the case of mild DR, the performances of the two models in terms of profit are quite close for both models, and no meaningful difference is observed (the profit under the linear model is 2.6% higher than the ANN-based model). However, as the price-responsivity of the AC agents increases (i.e., the system gets more uncertain), the superior predictive capability of ANN leads to higher profit levels for the retailer, compared to the linear model. For the case of active DR, the total profit of retailer per day is \$26.4 under the ANN-based model and \$23.9 under the linear model. Hence, using the ANN-based model leads to 10.5% improvement in the profit level of the retailer, compared to the linear model. The mean average difference between the optimal retail prices increases to the value of 3.1%. Also, for both DR cases, the ANN produces a more stable profit stream as is observed in the figures. Another notable result is that as the DR program gets

more active (i.e., the AC agents reduce their consumption costs more aggressively), the profit level of the retailer from the sales of energy also decreases (from 7.3% of total revenue for the case of mild DR to 4.8% for active DR). This drop is not only observed in the total profit, but also in the unit profit values (i.e., profit level per sold energy unit). For comparison, the total profit level of the retailer agent under no DR from loads is equal to \$96.4, which corresponds to 14.77% of the total revenue.

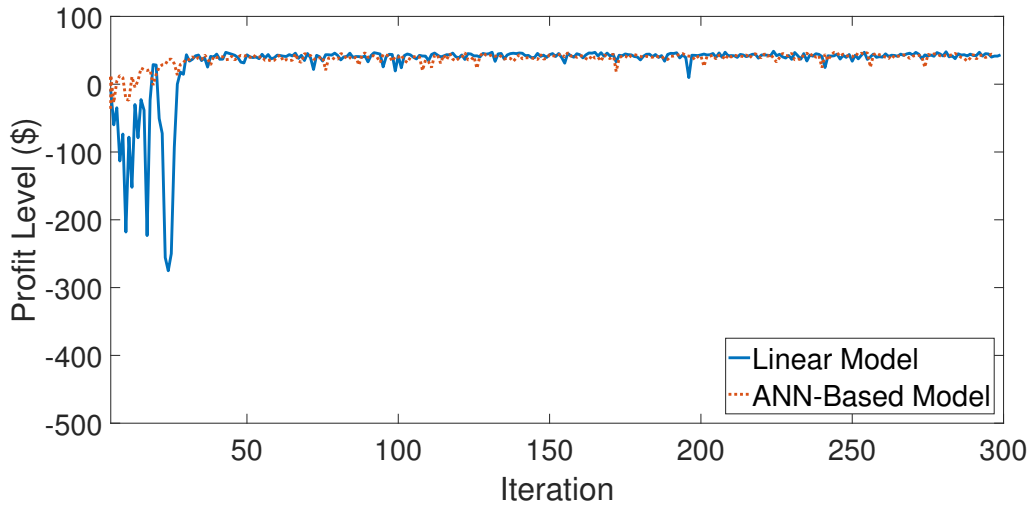


Figure 3.14: Retailer's profit throughout the iterations for the case of mild DR

The reduction in the profit level of the retailer, as the DR program gets more active, is due to the overall reductions in the cost of power consumptions as the consumers strategically modify their consumption profile in response to the retail prices they receive. This implies that as a result of the DR program, the consumers will be less captive to the actions of the profit-oriented retailers in the markets and are able to affect the equilibrium of the retail market to their benefit.

The final results of the optimization problems (i.e., optimal retail prices) are shown in Fig. 3.16, along with the input DA wholesale price signal (adopted from PJM data history [165]). By comparing the three cases of price-sensitivity (i.e.,

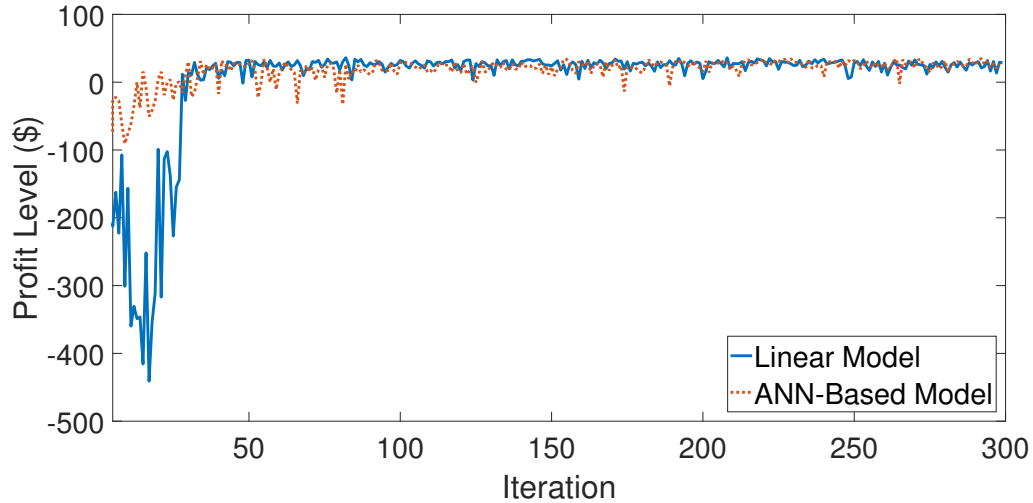


Figure 3.15: Retailer's profit throughout the iterations for the case of active DR

no-DR, mild DR, and active DR), it is observed that increased sensitivity of the consumers to consumption costs leads to smoother retail price signals. In Fig. 3.17 the correlation values between the wholesale and retail prices are shown. As can be seen, the correlation level between the two markets tend to increase as the demand response program gets more active.

Peak Shaving

Due to the shifting of AC loads towards the later hours of the day with lower energy prices, a minor secondary peak is created in the load profile around 19:00 PM to 21:00 PM, as shown in Fig. 3.9. While this minor peak is smaller than the main original peak of the load, in distribution systems with high penetration of PV generation the minor peak can contribute to network congestion and overloading (since there is a sharp drop in PV power around this period). Hence, we have also addressed the problem of peak load reduction using the dynamic pricing scheme in a distribution feeder with a high penetration of PV power (35% of the peak load). The

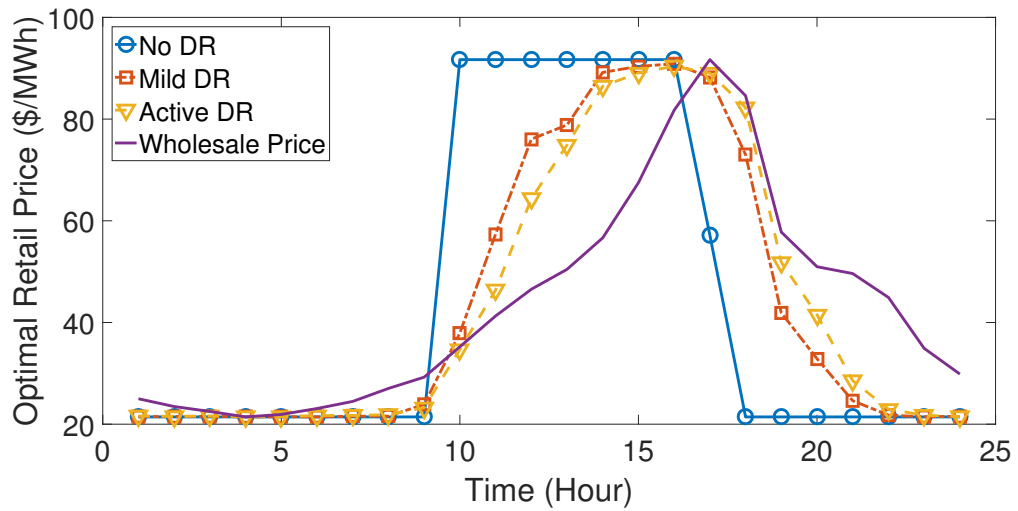


Figure 3.16: Optimal retail prices along with the wholesale price signal

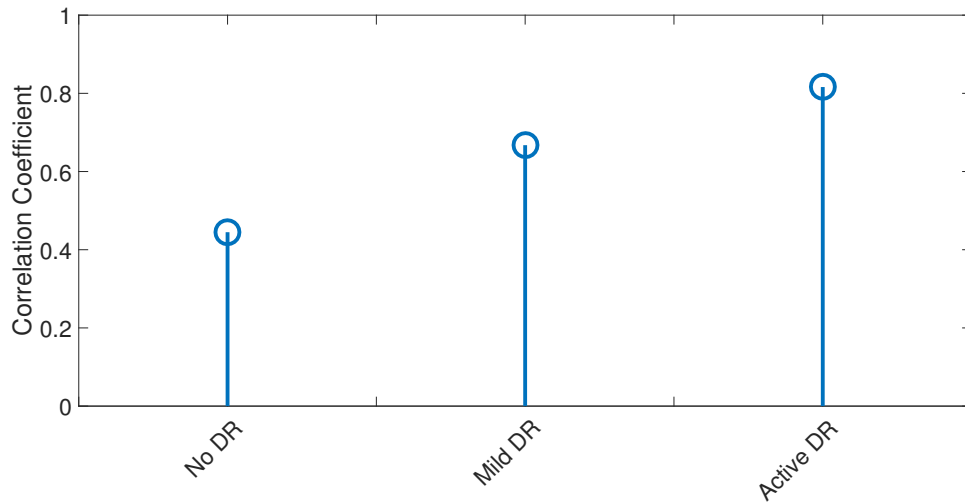


Figure 3.17: Correlation between the wholesale and retail prices as a function of price-sensitivity of loads

PV power profile used for the simulations is adopted from [59], and is shown in Fig. 3.18.

In this section simulations are performed, assuming that the goal of the retailer is to minimize peak load through optimal energy pricing by solving (3.12). The results show that employing the proposed pricing scheme in the distribution system with PV penetration, the retailer is able to reduce the estimated peak load value from 1.89 MW to 1.78 MW (mild DR) and 1.73 MW (active DR), as shown in Fig. 3.19. This implies that with 35% of the total load being price-sensitive AC loads in the distribution system, the peak load can be reduced by 5.5% (mild DR), and 8.5% (active DR). Hence, as the DR program gets more active higher levels of reduction in the peak load are achieved. Also, the peak-to-average load ratio (load factor) of the distribution feeder has improved from a value of 1.45 to around 1.39. It can also be observed from Fig. 3.19 that employing the proposed retail energy pricing mechanism to reduce peak load by the retailer does not lead to secondary peaks (unlike the original problem of the profit maximization).

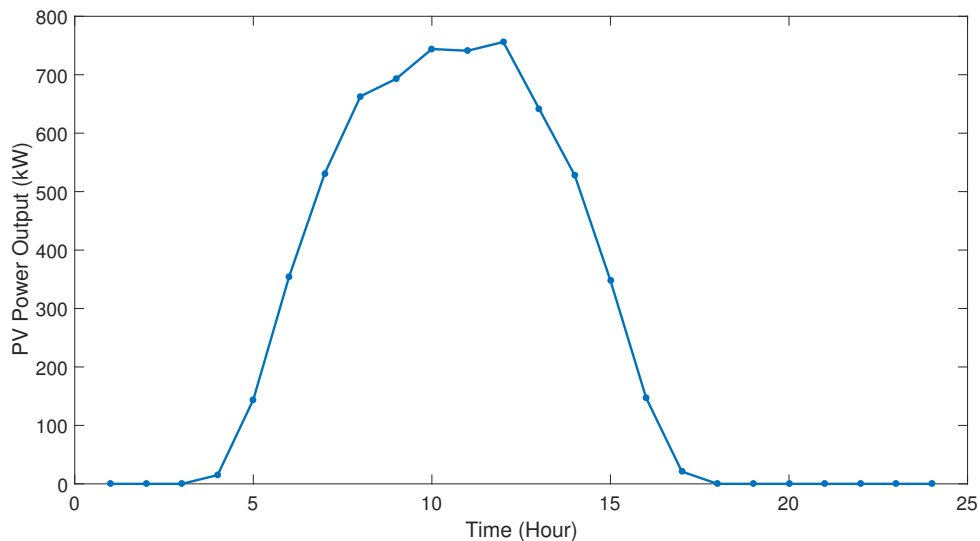


Figure 3.18: PV power profile in the distribution feeder

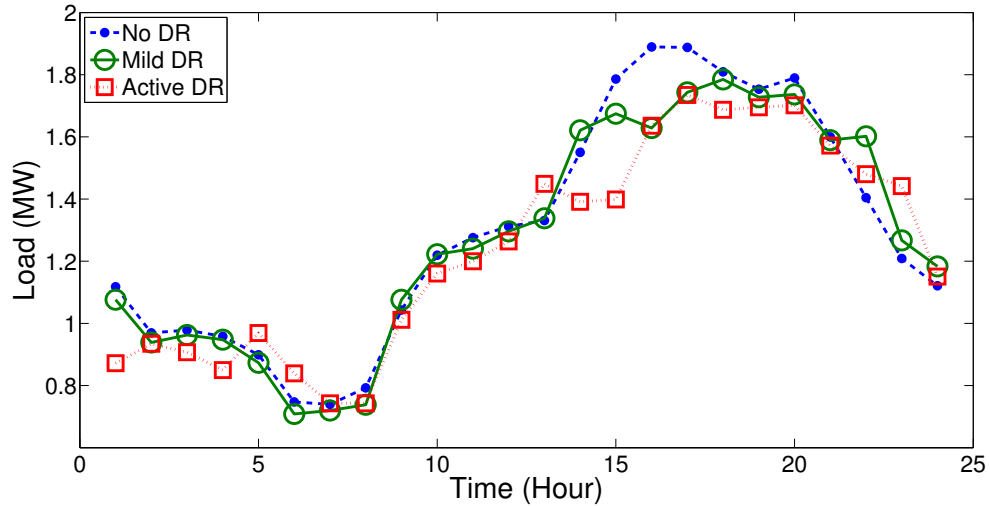


Figure 3.19: Feeder load profile, considering PV power generation under different DR scenarios

Conclusion

In this paper, we introduced an agent-based framework for studying the behavior of a DA retail market with DR from AC loads. The proposed approach employs machine learning techniques to model the behavior of the agents at different levels of the hierarchical framework. Q-learning is employed to solve the decision-making problem of the consumers. On the retailer side, different techniques (linear modeling and ANN-based modeling) are compared with each other, based on the linearity and non-linearity of the developed model by the retailer. Due to the modular characteristic of the proposed model, the framework can be generalized easily to include more complex and advanced models, without a need for significant changes in its basic functionality. The numerical results show that through this framework the consumers are able to cut their consumption costs, while the retailer maximizes its profit from the sales of energy, subject to the behavior of the loads in terms of cost-sensitivity.

Also, the results suggest that as the penetration level of price-sensitive appliances increases in the system (which leads to higher uncertainty), it would be beneficial (in terms of revenue) for the profit-oriented retailer to employ more advanced (non-linear) tools, such as ANNs, instead of a linear method, to capture the behavior of the consumers. As has been demonstrated in the paper, the same pricing mechanism can also be applied to reduce load peak value. The simulation results for high penetration of PV power in the retail market suggest that as the DR program gets more active, higher levels of peak reduction are observed.

INTELLIGENT MICROGRID POWER MANAGEMENT USING THE
CONCEPT OF NASH BARGAINING SOLUTION

Contribution of Authors and Co-Authors

Manuscript in Chapter 4

Author: Kaveh Dehghanpour

Contributions: Developed and tested the centralized MG power management model, and prepared the manuscript.

Co-Author: Hashem Nehrir

Contributions: Supervised the overall flow of the project, and provided important insight on numerical studies and interpretation of the results. Aided in the preparation of the manuscript.

Manuscript Information Page

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Abstract

In this paper, we propose a decision model for multiobjective power management of a generic MicroGrid (MG). The concept of Nash Bargaining Solution (NBS) from game theory is used by the central MG control unit to dispatch different resources within the MG. Using NBS, the MG is guaranteed to reach a solution on the Pareto-front of the multiobjective power management optimization problem. This solution is “unique” and introduces a “fair” balance among the different objective functions of the MG. Hence, through NBS, a multiobjective power management procedure is designed for MGs that can be implemented efficiently in real-time. Simulation results show the applicability of the proposed method to multiobjective MG power management.

Introduction

Electrical power systems are evolving into interconnected networks of various micro-sources, such as dispatchable and non-dispatchable distributed generation units, electrical vehicles, and controllable loads [191]. To manage and control these numerous active resources in the energy networks, the concept of MicroGrid (MG) [108] is employed. Basically, an MG is a small cluster of different micro-sources at the electricity distribution level. The main control unit of an MG is in charge of managing the micro-sources within the MG to achieve a desirable behavior throughout the system, by generating reference values for the local control agents of each micro-source in a way to maintain the power balance within the MG.

Given the intermittency and variability of renewable-based distributed generation units of an MG, the power management problem needs to be solved on a finer time scale, close to real-time system operation, to maintain the power balance in the

system [41]. Thus, it is essential to design a power management procedure that is numerically efficient and easy to be implemented in real-time.

In this paper, we address the problem of multiobjective power management of an MG, consisting of several micro-sources, including non-dispatchable renewable power generation. In general, the set of all solutions to a multiobjective optimization problem lies on the optimal trade-off curve among the different objective functions of interest [44]. This curve, which is composed of the set of non-dominated solutions to the optimization problem, is known as the *Pareto-front* [44]. Based on the previous works in the literature [32, 42, 174], in order to operate the MG, the Pareto-front of the multiobjective power management problem should first be obtained, usually through extensive bio-inspired and population-based evolutionary algorithms, such as Non-dominated Sorting Genetic Algorithm (NSGA-II) [44]. Even after obtaining the Pareto-front the question of selecting a “proper” operation point among the multitude of the final non-dominated solutions needs to be tackled with. Furthermore, as the number of objective functions increases this approach will become numerically burdensome for real-time applications.

In order to overcome this problem, in this paper we have proposed to employ the concept of bargaining games and Nash Bargaining Solution (NBS) [22] as a solution strategy to multiobjective power management problem of MGs. If the power management problem is modeled as a bargaining game among different objective functions, NBS is guaranteed to reach a unique point on the Pareto-front of the multiobjective optimization problem. Moreover, NBS is able to introduce a “fair” balance among different objective functions. Hence, by using NBS as a solution strategy to multiobjective power management problem of MGs we are able to avoid the complexities of obtaining the whole Pareto-front and choosing a solution among the final non-dominated solution set. The proposed power management procedure is

tested on an MG with various micro-sources, including diesel generator, Photo-Voltaic (PV) power generator, controllable loads (i.e., Demand Response (DR) [177]), and battery storage system.

The rest of the paper is constructed as follows: in Section II, a brief theoretical background of bargaining games and NBS is provided. In Section III, the NBS-based multiobjective power management strategy of MGs is introduced and described. Numerical results are given and discussed in Section IV. The conclusions of the paper are presented in Section V.

Bargaining Games and NBS

Within the context of game theory, bargaining is used to model situations of cooperative resource allocation among several players (agents) [132]. Hence, the players negotiate with each other to reach an agreement. More formally, a bargaining game has the following elements:

- A set of N agents, $\mathbf{Ag} = \{1, \dots, N\}$ that bargain with each other to find a globally agreeable solution to the bargaining game.
- A set of utility or pay-off functions, $\mathbf{U} = \{\mathbf{u}_1, \dots, \mathbf{u}_N\}$, where \mathbf{u}_i denotes the i^{th} player's pay-off level at each state of the bargaining game. The goal of each agent is to maximize its pay-off function through negotiations with its peers.
- A set of disagreement points, $\mathbf{D} = \{\mathbf{d}_1, \dots, \mathbf{d}_N\}$, where \mathbf{d}_i denotes the worst case pay-off value for the i^{th} player if the negotiations break down. Hence, the disagreement points represent the tacit threat of inability of agents to reach an agreement. If the bargaining game is well-defined (i.e., the disagreement points have worse performance than every other solution) and the agents are "rational" then the disagreement point is never reached.

It has been shown that a bargaining game, defined above, has a set of rational solutions. These solutions constitute the Pareto-front of the pay-off functions of different players [132]. Intuitively, if a solution on the Pareto-front is reached, no agent can further improve its pay-off value unless at the expense of at least one other player. Hence, deviation from each point on the Pareto-front will be met by objection from at least one player. This implies that the Pareto-front in the utility space of the agents is basically the set of equilibria to the bargaining game.

Now the question is which solution or equilibrium among the multitude of rational solutions on the Pareto-front should be chosen as the outcome of the bargaining game. To answer this question different solution strategies have been proposed in the literature [132]. However, despite all the critiques, the most widely used solution concept to bargaining games is the NBS. The reason for this wide range of applications for NBS is its desirable and advantageous properties (discussed below).

The properties of NBS are as follows [132]:

- **Calculation:** NBS can be obtained using optimization problem (4.1). This optimization problem is solved over the feasible solution set within the pay-off space of the players (\mathbf{F}_U).

$$\mathbf{NBS} = \arg \min_{(\mathbf{u}_1, \dots, \mathbf{u}_N) \in \mathbf{F}_U} - \prod_{i=1}^N (\mathbf{u}_i - \mathbf{d}_i). \quad (4.1)$$

- **Uniqueness:** If \mathbf{F}_U is a convex set (i.e., the bargaining game is convex) then (4.1) is a convex optimization problem and NBS is the global optimum to the problem and is unique.
- **Efficiency:** Given a convex bargaining game, NBS (obtained through (4.1)) is guaranteed to be Pareto-optimal (i.e., NBS lies on the Pareto-front of the

bargaining game).

- **Fairness:** If the bargaining game is symmetric with respect to players i and j (i.e., if $(\mathbf{u}_i = \mathbf{u}, \mathbf{u}_j = \mathbf{u}') \in F_U$ then $(\mathbf{u}_i = \mathbf{u}', \mathbf{u}_j = \mathbf{u}) \in F_U$), then those players will receive the same pay-off value with NBS. This means that NBS does not discriminate between identical players.
- **Covariance under positive affine transformation:** NBS is independent of unit of measurement of the pay-off functions of the players.
- **Independence of irrelevant alternatives:** NBS is insensitive to changes in the set of inferior alternative solutions.

MG Power Management Strategy

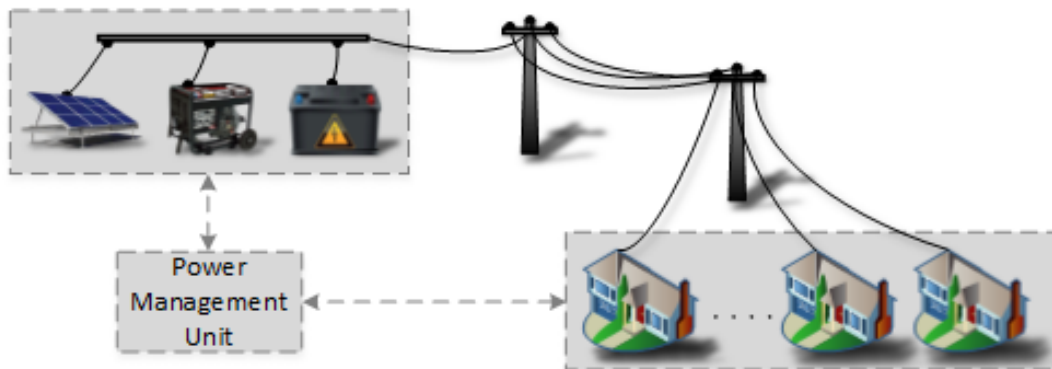


Figure 4.1: The overall architecture of an MG

[167]

MG Structure

The structure of a generic MG is shown in Fig. 4.1. As can be seen in this figure the system is composed of different micro-sources, including PV power

generator, diesel generator, lead-acid battery storage system, controllable loads (local DR resources), and uncontrollable fixed load. The produced/consumed powers of the diesel generator ($\mathbf{P}_{DG}(\mathbf{t})$), the battery system ($\mathbf{P}_{ESS}(\mathbf{t})$), and the DR resources ($\mathbf{P}_{DR}(\mathbf{t})$) are assumed to be controllable at time \mathbf{t} , within a decision horizon of length \mathbf{T} ($\mathbf{t} = \mathbf{1}, \dots, \mathbf{T}$). Also, the value of power exchange with the main grid through the PCC ($\mathbf{P}_G(\mathbf{t})$) is controlled. We assume that the PV power ($\mathbf{P}_{PV}(\mathbf{t})$) is based on the maximum power point tracking of its local controller, and given as input in the decision model. Also, the power consumption of fixed (base) load ($\mathbf{P}_f(\mathbf{t})$) is assumed to be uncontrollable.

For real-time operation, based on forecasted values of load and PV power, the power management problem is solved at $\Delta\mathbf{t}$ intervals with the look-ahead time of $\mathbf{T} \cdot \Delta\mathbf{t}$. After each $\Delta\mathbf{t}$ the decision window moves along time (with $\Delta\mathbf{t}$ steps) and the forecasted values of fixed load and renewable power are updated based on new data available to prediction units. In this paper, the PV power and load forecasting distribution errors are selected according to [222], and [75], respectively. Basically, only the signals within the first slice of the decision window (at $\mathbf{t} = \mathbf{1}$) are sent to local controllers of different micro-sources as reference signals for immediate system operation. The signal values in the rest of the decision window are used as initial condition for the next steps of power management, providing good start for the optimization solver. In this paper, the power management problem is solved in 5-minute intervals, within a look-ahead moving decision window of 4 hours (i.e., $\Delta\mathbf{t} = 5 \text{ min}$, $\mathbf{T} = 48$).

NBS-Based Multiobjective Optimization

The multiobjective power management problem is modeled as a bargaining game, among the different players. The pay-off function of each player is an objective

function of interest to the power management problem of the MG. The concept of NBS is used to solve the bargaining game and obtain a “unique”, “fair”, and Pareto-optimal solution for the multiobjective optimization problem. Note that since NBS is independent of the unit of measurement of the pay-off functions of the players, it is legitimate to consider different objective functions (with different units) as pay-off functions of the players. Hence, by employing NBS we are able to avoid calculating the whole Pareto-front and considerably reduce the computational load of the power management problem.

The objective functions of interest considered for system operation in this paper, are as follows:

- **Average profitability of local power generation:** Assuming that power can be sold back to the grid, the sources of revenue and cost are as follows:

$$C_1 = \frac{1}{L} \cdot \sum_{t=1}^T (a \cdot P_{DG}(t)^2 + b \cdot P_{DG}(t) + c) \quad (4.2)$$

$$R_1 = \frac{1}{L} \cdot \sum_{t=1}^T (-\lambda \cdot P_G(t)) \quad (4.3)$$

$$R_2 = \frac{1}{L} \cdot \sum_{t=1}^T (\lambda \cdot P_{DR}(t)), \quad (4.4)$$

where, C_1 represents the average power production cost for the diesel generator. As can be seen and according to [167], the cost characteristic of the diesel generator is approximated by a quadratic cost function with parameters a , b , and c . Also, L represents the temporal length of the decision window. R_1 , and R_2 denote the average revenue through sales of energy to the main grid, and cost savings through DR, respectively. λ represents main grid energy price.

Thus, the average MG profit is calculated as follows:

$$f_1 = R_1 + R_2 - C_1. \quad (4.5)$$

- **Average diesel generator efficiency:** Based on [167], the average efficiency of the diesel generator, as a function of its output power can be written as:

$$f_2 = \frac{1}{L} \cdot \sum_{t=1}^T \left(\frac{k \cdot P_{DG}(t)}{a \cdot P_{DG}(t)^2 + b \cdot P_{DG}(t) + c} \right), \quad (4.6)$$

where, k is a coefficient calculated based on discussions in [167]. Note that the efficiency is a concave function in P_{DG} .

- **Average demand-side utility:** As has been discussed in the literature [60, 177], different types of concave utility functions can be used to model how the consumers value the energy they consume. In this paper, we have chosen an exponential utility function (f_3) to model the aggregate reaction of consumers to changes in the power consumption levels.

$$f_3 = \frac{1}{L} \cdot \sum_{t=1}^T (\lambda \cdot P_f(t) \cdot (1 - e^{-\omega(P_f(t) - P_{DR}(t))})), \quad (4.7)$$

where, ω represents the aggregate consumers' willingness to cut power consumption levels. For a more detailed discussion on exponential utility functions, refer to [60].

Based on the objective functions introduced above, the NBS-based multiobjec-

tive power management optimization is as follows:

$$\begin{aligned}
& \min_{\mathbf{P}} \left\{ -\log \prod_{i=1}^N (f_i(\mathbf{P}) - d_i) \right\}, \\
& \text{s.t. } P_{DG}(t) + P_{PV}(t) + P_G(t) + P_{ESS}(t) + P_{DR}(t) = P_f(t), \\
& \quad P_{DG}^{min} \leq P_{DG}(t) \leq P_{DG}^{max}, \\
& \quad |P_{DG}(t) - P_{DG}(t-1)| \leq GRC, \\
& \quad P_G^{min} \leq P_G(t) \leq P_G^{max}, \\
& \quad P_{DR}^{min} \leq P_{DR}(t) \leq P_{DR}^{max}, \\
& \quad P_{ESS}^{min} \leq P_{ESS}(t) \leq P_{ESS}^{max}, \\
& \quad SOC(t) = SOC(t-1) - \frac{\Delta t}{E_{max}} \cdot P_{ESS}(t), \\
& \quad SOC^{min} \leq SOC(t) \leq SOC^{max}, \\
& \quad \forall t = 1, \dots, T,
\end{aligned} \tag{4.8}$$

where in (4.8), the objective function of the global optimization problem consists of a product of local objective functions ($f_i(\mathbf{P})$) with their individual disagreement points (d_i), which define worst case scenarios from the perspective of each objective function. The decision variable \mathbf{P} denotes the vector of the controllable power variables. P_{DG}^{min} , and P_{DG}^{max} are the minimum and maximum power capacity of the diesel generator. Similarly, P_{DR}^{min} , P_{DR}^{max} , P_{ESS}^{min} , and P_{ESS}^{max} define the minimum and maximum power limits of the controllable loads and the battery system (note that for the battery, $P_{ESS}^{min} \leq 0$, which defines the maximum battery charging rate). GRC denotes the Generation Rate Constraint, which is the maximum ramp rate of the diesel generator unit. The State Of Charge (SOC) of the battery should also be kept between its minimum (SOC^{min}) and maximum (SOC^{max}) limits at all times, t , to ensure that the stored energy of the battery is within a reasonable fraction of its total energy

capacity (\mathbf{E}_{max}). Note that the power losses in the battery are ignored. Since the objective functions are concave in decision variables, the overall optimization problem (4.8) is convex, and NBS is well-defined [26]. Note that in (4.8), the disagreement points (\mathbf{d}_i) define the worst case scenarios for each objective function.

Simulation Results

The proposed power management strategy has been tested on a slightly modified version of the MG used in [167], shown in Fig. 4.1. The PV power output is based on the measurements provided in [59] and shown in Fig. 4.2 for a whole day. The fixed load data is adopted from [110] and depicted in Fig. 4.3. The parameters of different micro-sources are shown in Table 4.1.

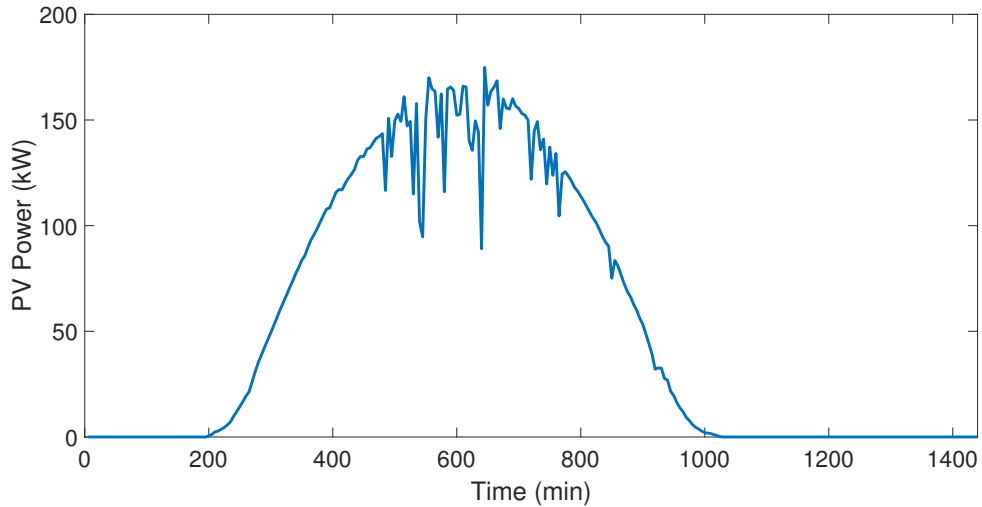


Figure 4.2: PV power generation profile

NBS Calculation Verification

To verify that the NBS obtained using (4.8) lies on the Pareto-front of the multiobjective power management problem, the problem has been solved with the

Table 4.1: MG Parameters

Parameter	Value
a	$1.06 \cdot 10^{-4} \text{ \$/kWh}^2$
b	$0.102 \text{ \$/kWh}$
c	$8.802 \text{ \$}$
λ	$0.09 \text{ \$/kWh}$
ω	3
P_{DG}^{min}	0
P_{DG}^{max}	350 kW
GRC	$5\%/min$
P_G^{min}	$-30\% \cdot P_{DG}^{max}$
P_G^{max}	$+30\% \cdot P_{DG}^{max}$
P_{DR}^{min}	0
P_{DR}^{max}	$25\% \cdot P_f$
P_{ESS}^{min}	-100 kW
P_{ESS}^{max}	100 kW
SOC^{min}	0.3
SOC^{max}	0.9
E^{max}	850 kWh

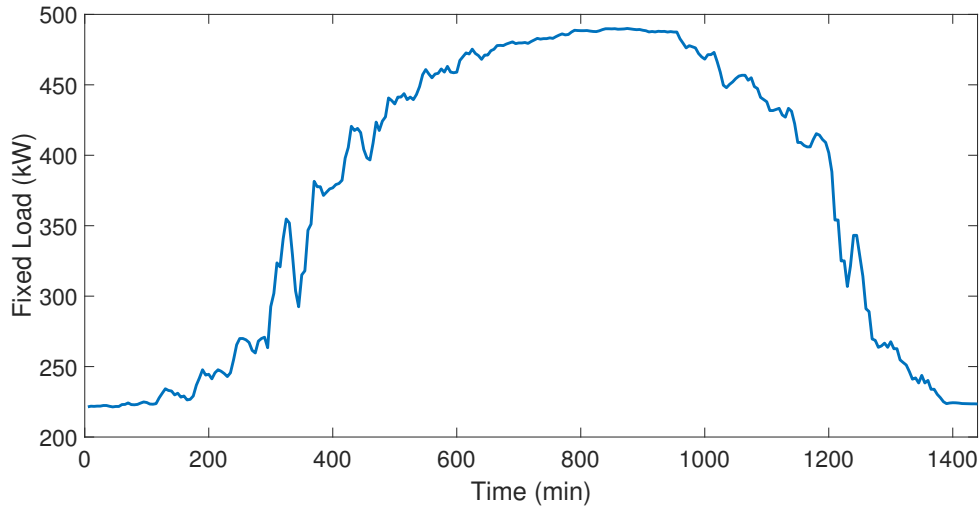


Figure 4.3: Base load profile

three introduced objective functions (profit, efficiency, and the demand utility). The Pareto-front of the power management problem is also calculated using the weighted sum approach, as discussed in [44]. The three-dimensional Fig. 4.4 shows the Pareto-front trade-off solutions to the multiobjective power management problem, as well as the NBS obtained using (4.8). As can be observed from the figure, the obtained NBS is actually located on the underlying Pareto-front of the multiobjective power management problem, as expected. Pareto-optimality is achieved for each round of bargaining over the decision horizon for the system.

Power Management Results

In this section, the results of the real-time power management problem (performed each $\Delta t = 5 \text{ min}$) are shown and discussed. In Fig. 4.5 the output power of the diesel generator is shown. As can be seen from this figure, the highest contribution of the diesel generator occurs at the high peak load time period. Also, due to the ramp rate constraint the diesel requires some time to catch up with the

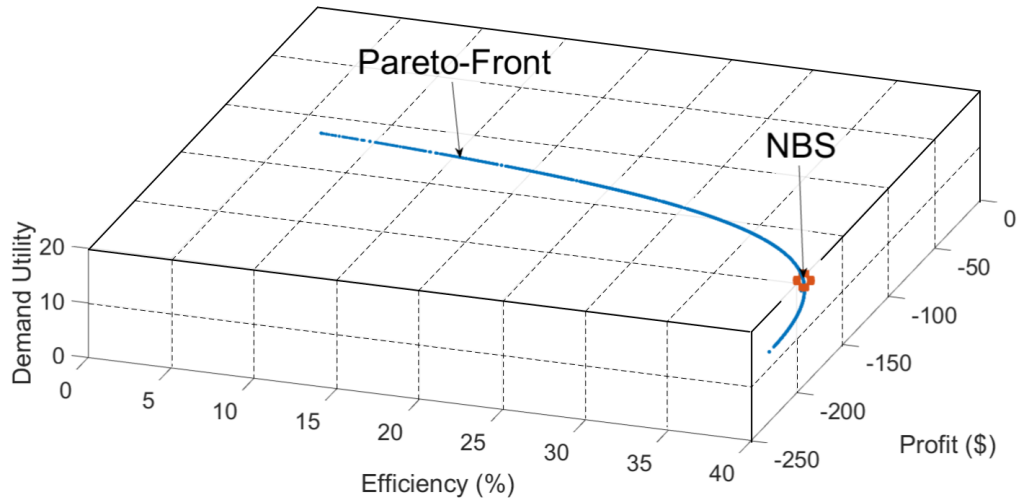


Figure 4.4: NBS location with respect to the Pareto-front

peak load. Moreover, this ramp rate constraint does not permit the diesel generator to react to the high frequency fluctuations of the PV power output. On the other hand, the battery system is able to absorb the PV power fluctuations, due to its fast response time. The power output of the battery system is depicted in Fig. 4.6, with positive and negative values indicating discharging and charging, respectively. The stored energy of the battery system is shown in Fig. 4.7. As can be seen the stored energy level is always kept between the maximum and minimum SOC limits. Apart from absorbing the variability of the PV power, the battery system also contributes to the peak load values. The aggregate load value (including both the DR resources and the fixed load) is demonstrated in Fig. 4.8, with respect to the fixed load profile. As can be seen in this figure DR leads to reduction in load level at peak hours. The reduction in load reaches a maximum value of %9.6 during peak hours. Except for the peak load period, DR resources are not employed in the rest of hours of the day. The exchanged power with the main grid is shown in Fig. 4.9. Note that positive exchanged power with the main grid implies importation of power into the

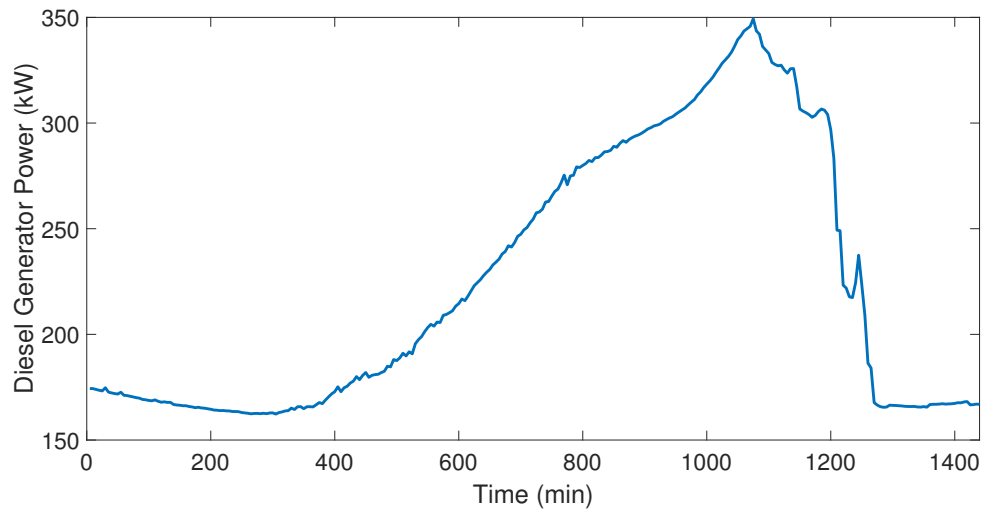


Figure 4.5: Diesel generator's power profile

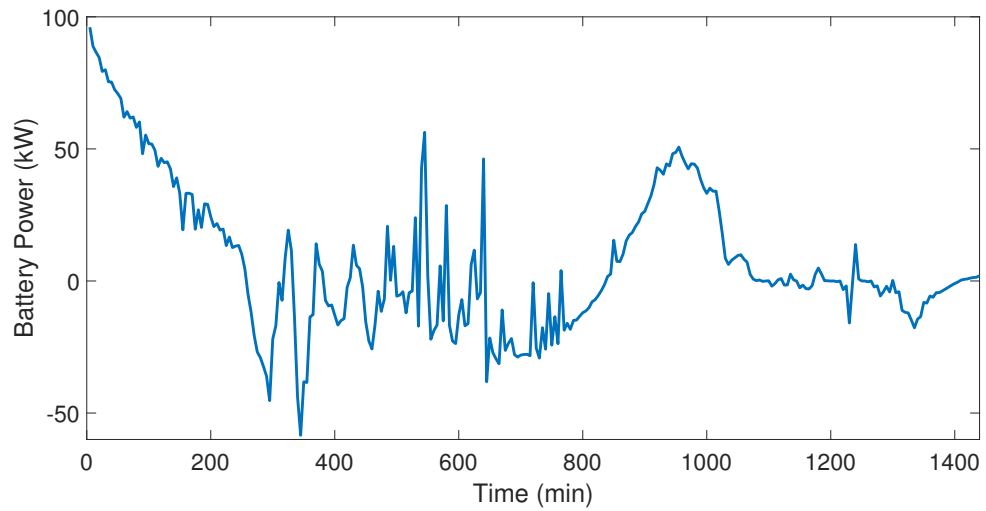


Figure 4.6: Battery storage system's power profile

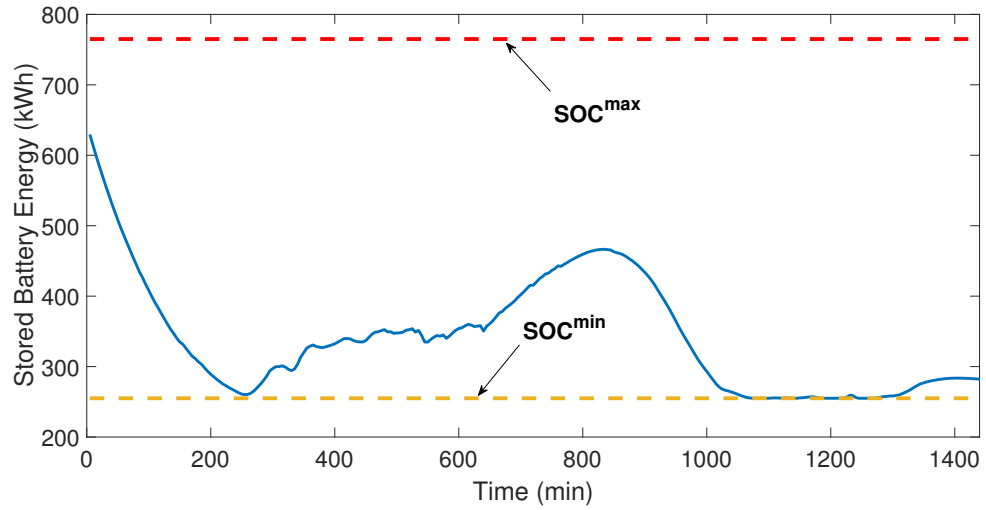


Figure 4.7: Stored energy level in the battery system

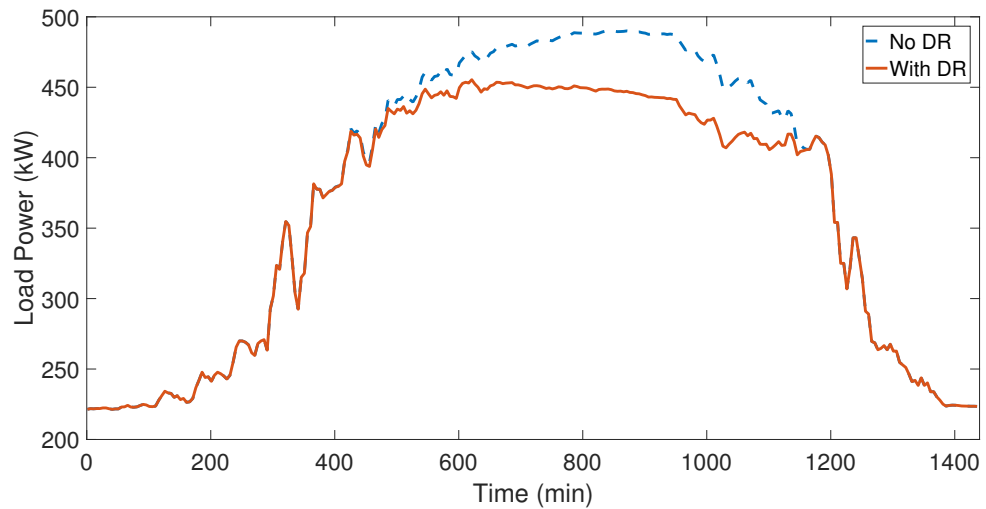


Figure 4.8: Demand profile of the MG with and without DR

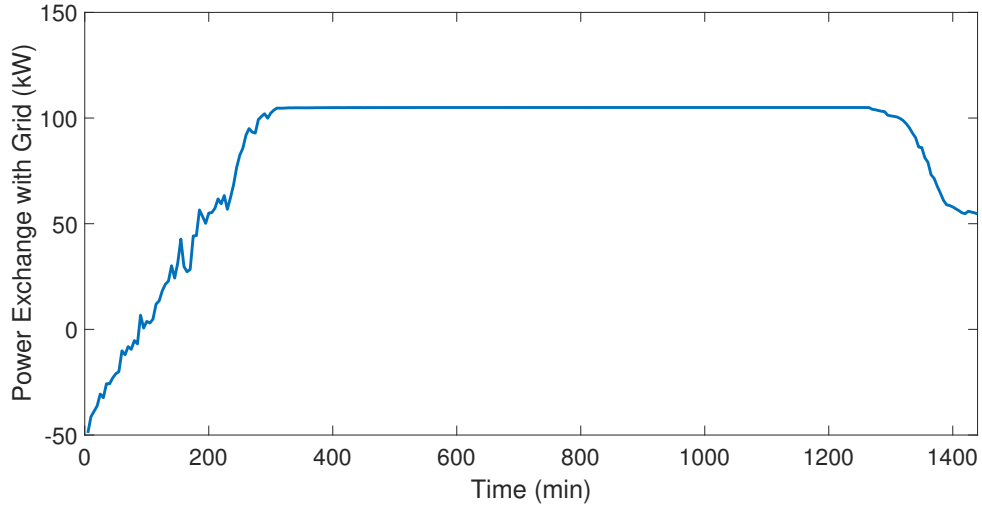


Figure 4.9: Power exchange of the MG with the main grid

MG. The power importation rate increases until it reaches its maximum permissible value (P_G^{max}). Also, as can be seen from this figure, the grid does not “observe” the volatility of the PV power, since it is absorbed by the local energy storage unit. Hence, the profile of the exchanged power with the grid is almost uniform and smooth.

Conclusion

In this paper, we have proposed a multiobjective power management procedure for MGs based on the concept of NBS. The proposed power management procedure is able to track a unique Pareto-optimal solution that introduces a fair balance among the different objective functions of the micro-sources of the MG. The proposed method has been tested and verified on an MG model, for real-time power management.

REAL-TIME MULTIOBJECTIVE MICROGRID POWER MANAGEMENT
USING DISTRIBUTED OPTIMIZATION IN AN AGENT-BASED BARGAINING
FRAMEWORK

Contribution of Authors and Co-Authors

Manuscript in Chapter 5

Author: Kaveh Dehghanpour

Contributions: Developed and tested the distributed bargaining framework for microgrid power management, and prepared the manuscript.

Co-Author: Hashem Nehrir

Contributions: Supervised the overall flow of the project, and provided important insight on numerical studies and interpretation of the results. Aided in the preparation of the manuscript.

Manuscript Information Page

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Abstract

In this paper, we propose a Multi-Objective Power Management (MOPM) procedure for MicroGrids (MG). Through this procedure the power management problem is modeled as a bargaining game among different agents with different sets of objective functions. Nash Bargaining Solution (NBS) is employed to find the solution of the bargaining game. NBS lies on the Pareto-front of the power management problem. Moreover, it introduces a unique and fair balance among the objective functions of different agents and removes the need to track the whole Pareto-front in real-time. Distributed Gradient Algorithm (DGA) is applied to find the NBS through a modular distributed decision framework without using a central control unit. In this way, the problem of data privacy of different parties within the MG is addressed. The proposed methodology has been tested through simulations on islanded and grid-connected MGs under different pricing scenarios (fixed versus Time-of-Use (ToU) pricing).

Introduction

The growth of renewable energy resources in the form of distributed on-site generation has led to the introduction of the concept of MicroGrid (MG) [40]. An MG is basically a small-scale cluster of different types of controllable and uncontrollable microsources connected together at electrical distribution level. These microsources include on-site generators (both Variable Renewable Sources (VRS) and non-renewable Dispatchable Generators (DG)), Energy Storage Systems (ESS), and fixed and controllable loads (i.e., Demand Response (DR)) [168]. Each MG can be thought of as a self-sustainable energy unit with its own decision-making and control capabilities, which is able to continue operating and serving consumers even when

it is islanded from the main grid. Hence, MGs not only enable the penetration of renewable energy resources at the electrical distribution level, but also introduce some level of “resiliency” into the power grid due to their islanding capability [100].

In order to utilize an MG, a hierarchical control and decision-making structure is required [76]. At the lower level of this hierarchy each microsource within the MG employs a local control unit (which is usually based on droop characteristics [105]). At the higher level of the hierarchy the local controllers are coordinated by a power management process to reach a desirable global behavior throughout the MG. Basically, the power management apparatus provides reference signals for the lower-level control systems. In this paper we propose and investigate a novel agent-based power management procedure which can be applied to both grid-connected and islanded MGs.

Most of the power management procedures proposed in the literature are aimed at single-objective optimization, namely, total operational cost minimization [19] or power loss minimization [143]. However, in general, the power management problem within an MG can have several competing objective functions. Hence, different microsourses of an MG can have different objectives or sets of objective functions. Compared to a single-objective approach, the proposed Multi-Objective (MO) optimization formulation allows us to reach trade-off solutions among several competing objective functions (e.g., cost savings/comfort level, efficiency/profit) and explicitly consider the effect of different objective functions within system operation. The goal of Multi-Objective Power Management (MOPM) optimization problem of MGs is to find the set of non-dominated optimal trade-off solutions, known as the Pareto-front of the optimization problem [44]. In [32] a MO linear programming approach is proposed for MG power management using multi-layered Artificial Neural Networks (ANN). Another MOPM technique is introduced in [235] employing Non-

dominated Sorting Genetic Algorithm (NSGA-II) to obtain the Pareto-front of the optimization problem. In [174], different objective functions are also considered in energy management of an MG with high penetration of renewable power sources, through valuation functions. In another work, the Pareto-front of the objective functions of an MG is obtained using a sampling approach and an agent-based model [42]. Also, in [114] the MOPM problem of MGs is modeled and solved as a static non-cooperative game.

While in the previous works the whole Pareto-front is obtained through sampling, point-by-point optimization, or evolutionary population-based algorithms, these approaches can be numerically burdensome for real-time applications as the number of objective functions increases. Hence, to address this problem, in this paper we propose a power management approach that is able to find a “unique” and “fair” solution to the MOPM problem of MGs without the need to track the whole Pareto-front in real-time. A fair solution strategy should not discriminate between the objectives (i.e., under symmetric conditions it should yield identical results for different objectives). The proposed power management procedure is based on the idea of Nash Bargaining Solution (NBS) [132]. Hence, The MO optimization problem can be viewed as a bargaining game consisting of different agents (players) with different sets of objective functions. Each controllable microsource within the MG is assigned an agent which participates in the bargaining process on behalf of the parties in charge of the microsourses. Thus, MG is modeled as a cooperative community of producers and consumers, where each entity is interested in obtaining a trade-off between its available objective functions and the objective functions of other agents (while maintaining the overall cooperative nature of the decision problem). NBS is selected as a solution strategy since it was designed to address situations of cooperative decision making with bargaining, which is essential in the case of an MG

power management model.

Due to its advantages, NBS has been used in different industry-related applications with the goal of fair resource allocation; a few examples are as follows: bandwidth, sub-carrier, and power allocation along with relay cooperation in communication systems [234] [81] [160], developing licensing policies [104], designing permit allocation rules for pollution control [96], marriage market and household labor studies [38], and traffic control [186].

The NBS of a bargaining game lies on the Pareto-front of the pay-off functions (i.e., objective functions) of the agents in the game. Apart from its uniqueness, NBS introduces a fair balance among the objective functions of the agents. We have shown in [47] that the NBS of the MOPM problem of an MG can be computed using a central optimization method. In this paper, we will demonstrate that the NBS of the bargaining game can be obtained through a Distributed Sum Optimization (DSO) problem [147] which can be solved using an agent-based platform via a distributed optimization technique. The employed solution technique is known as Distributed Gradient Algorithm (DGA) [147, 149, 150], which was selected due to its ease of implementation and its desirable mathematical properties. Using DGA different control agents (with different objective functions) within a communication network are able to interact and exchange data with each other to solve a DSO problem, cooperatively, without a central solver. While DGA has already been applied for solving power engineering optimization problems [232], its use has been limited to single-objective optimization problems. In this paper, we extend DGA to a distributed bargaining situation to solve the MOPM problem of MGs. Thus, unlike previous MOPM methods in the literature, the proposed approach is modular and distributed by nature. In this way, a distributed bargaining framework is designed through which the data privacy of different parties within the system is respected

(i.e., to reach a solution, the agents do not need to share their private cost/utility and feasible decision region with each other). Also, by removing a central control unit, we are basically removing a single point of failure. This implies that a more secure system automation with plug-and-play capabilities can be achieved through the proposed distributed optimization framework. Using a distributed reasoning approach, we obtain an inter-operable system with plug-and-play capabilities [56]. This bargaining framework enables the agents to reach a fair agreement which lies on the Pareto-front of the MOPM problem. To demonstrate the efficiency of the framework, the proposed method is tested on both islanded and grid-connected MGs through numerical simulations under fixed and Time-of-Use (ToU) pricing scenarios.

To summarize, the contributions of the paper are as follows:

- Using game theory, the MG is modeled as a community of cooperative agents with competing objective functions that bargain with each other to reach a fair and Pareto-efficient outcome.
- The bargaining process, which is basically the MOPM of the MG, is solved using the concept of NBS, which provides desirable properties: uniqueness, fairness, and Pareto-efficiency.
- The computational process is performed through an agent-based distributed optimization framework, without a central control unit. Employing this framework, the agents are able to reach the NBS, without sharing their private cost and constraint data.

The rest of the paper is constructed as follows: in Section II the overall structure of the MOPM problem of MGs is discussed. The distributed bargaining/optimization framework is designed in Section III. The results of the numerical experiments are

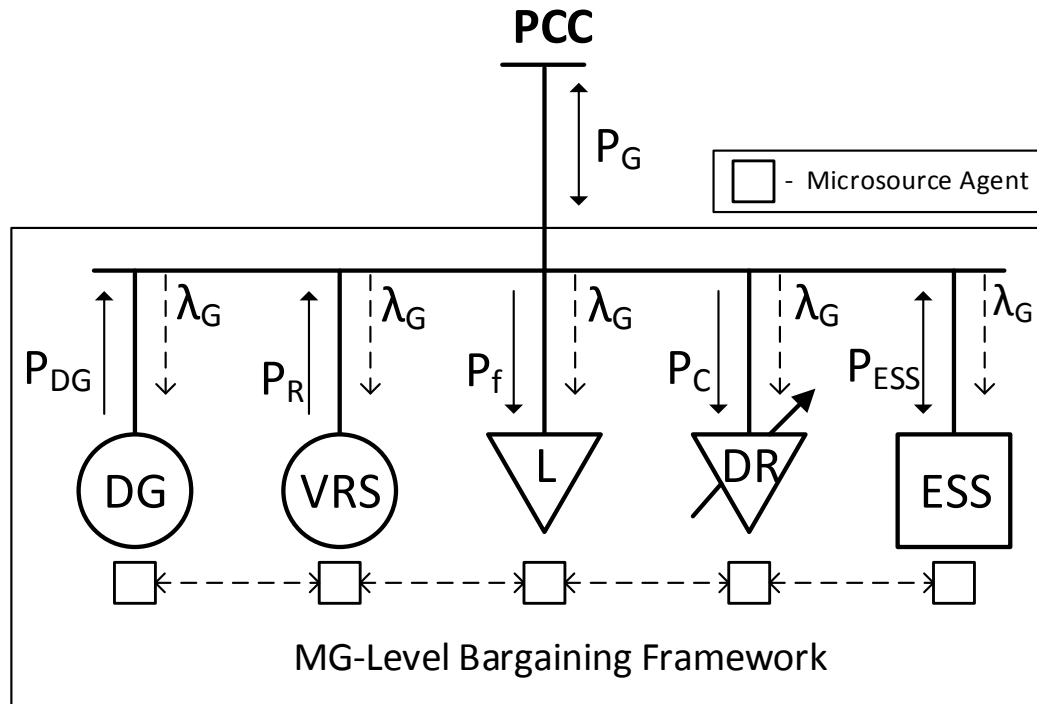


Figure 5.1: Generic MG architecture

shown and discussed in Section IV. The conclusions of the paper are presented in Section V.

MG Power Management Problem

In this section the agent-based MOPM problem is discussed in details. A generic MG consisting of different microsources is shown in Fig. 5.1. Each microsource is equipped with a control agent which participates in the MG-based bargaining framework on behalf of the element. The microsources considered in this paper are: thermal DG unit, battery storage bank, DR resources (consisting of curtailable and

time-shiftable loads), Photo-Voltaic (PV) power generator, and fixed uncontrollable loads. Note that the control agents within the MG are “price-takers” (due to their relatively small size and low market share). Hence, the price signals (both the fixed and ToU tariffs) are the input variable to the decision model, which are set by a power utility company.

Timing Strategy and Uncertainty Handling

In this paper we have adopted a rolling horizon optimization strategy [19]: at each time instant (\mathbf{t}) the power management problem is solved for a certain look-ahead time ($\mathbf{t} + \mathbf{T}$), based on forecasted values for renewable energy resources and the load. The decision horizon is divided into \mathbf{H} time steps ($\Delta\mathbf{t}$). The goal of the power management problem is to optimize the decision variables (i.e., output power of the controllable microsourses) at different time steps of the decision window. After the power management problem is solved, the values of the decision variables corresponding to the immediate time step ($\mathbf{t} + \Delta\mathbf{t}$) are sent to the local control devices of the microsourses. The values of the decision variables for the rest of the decision horizon can be stored as back-up or be used as initial conditions in future rounds of the power management optimization (i.e., hot start). Then the decision window is rolled one step ahead (i.e., $\mathbf{t} := \mathbf{t} + \Delta\mathbf{t}$).

As discussed above, the values of certain variables (fixed load and PV power) need to be forecasted and used in the power management problem. The prediction error is a source of uncertainty in the decision making. In this paper, two such sources of uncertainty are considered in the modeling: prediction error of renewable energy sources and load prediction error. These errors are represented by Gaussian distribution functions which are adopted from [222] and [75]. Note that the distribution of forecasting error changes at different time steps of the decision horizon.

Hence, as the decision window rolls through time the forecasted values of the load and renewable power are also updated based on the time-varying distribution functions of the prediction error.

Problem Formulation

The objective functions and constraints of different microsources considered in the power management problem are discussed in this subsection. The objective functions are denoted as U_i^j , indicating the j^{th} objective of the i^{th} microsource.

1. **DG unit:** Two objective functions are considered for the DG unit: total profit (i.e., total revenue less total cost) from local power generation (U_1^1) and average efficiency (U_1^2).

$$U_1^1 = \sum_{t=1}^H \{-P_G(t)\lambda_G(t) - (a \cdot P_{DG}(t)^2 + b \cdot P_{DG}(t) + c)\} \quad (5.1)$$

$$U_1^2 = \frac{1}{H} \cdot \sum_{t=1}^H \left\{ \frac{k \cdot P_{DG}(t)}{a \cdot P_{DG}(t)^2 + b \cdot P_{DG}(t) + c} \right\} \quad (5.2)$$

where, coefficients \mathbf{a} , \mathbf{b} , and \mathbf{c} define the quadratic cost function of the DG, according to [167]. P_{DG} , P_G , and λ_G denote the output power of the DG unit, power import from the main grid, and the grid price value, respectively. Objective function (5.1) is composed of two terms: the cost/revenue of power exchange with the grid and the cost of local power generation using the DG unit. Hence, this objective function defines the profitability of power production from the DG unit. The reason that the DG control agent is considered to be in charge of this objective is that this agent has direct access to DG cost data. Note that depending on the sign of the power exchanged with the grid at the PCC, the first term in objective function (5.1) (i.e., $-\lambda_G P_G$) can be positive or negative

(i.e., $P_G \geq 0$ implies power import from the grid, and $P_G \leq 0$ implies power export to the grid). Hence, the first term in objective function (5.1) can be both revenue (for $P_G \leq 0$) or cost (for $P_G \geq 0$). When the DG is isolated from the main grid, since the revenue from sales of power to grid is eliminated, U_1^1 turns into the negative cost of production. The efficiency equation (5.2) is also adopted from [167], along with the expression for the coefficient k used in (5.2), defined as:

$$k = \frac{3600 \cdot \lambda_F}{E_C} \quad (5.3)$$

where, λ_F and E_C are the unit price of fuel and fuel energy density for the DG unit, respectively. The constraints on the DG unit are as follows:

$$P_{DG}^{min} \leq P_{DG}(t) \leq P_{DG}^{max} \quad (5.4)$$

$$\frac{|P_{DG}(t) - P_{DG}(t-1)|}{\Delta t} \leq GRC \quad (5.5)$$

where, (5.4) gives the production limits on output power of the DG ($[P_{DG}^{min}, P_{DG}^{max}]$).

The Generation Rate Constraint (GRC) is enforced by (5.5). This constraint defines the ramp rate limit of the thermal DG unit.

2. **ESS unit:** In this paper, no objective function is considered for the battery storage system. However, the following constraints are taken into account:

$$P_{ESS}^{min} \leq P_{ESS}(t) \leq P_{ESS}^{max} \quad (5.6)$$

$$SOC(t) = SOC(t-1) - \frac{\Delta t}{E_{max}} \cdot P_{ESS}(t) \quad (5.7)$$

$$\mathbf{SOC}^{min} \leq \mathbf{SOC}(t) \leq \mathbf{SOC}^{max} \quad (5.8)$$

where, positive and negative values for the output power of the ESS (\mathbf{P}_{ESS}) define discharging and charging states, respectively. \mathbf{E}_{max} denotes the energy capacity of the battery system. The normalized State Of Charge (SOC) of the battery is determined as (5.7) and maintained within its boundaries ($[\mathbf{SOC}^{min}, \mathbf{SOC}^{max}]$). Note that the power losses of the battery system are ignored, which is reasonable for high energy efficiency battery systems.

3. Demand Response Provider (DRP) unit: The DRP is a load aggregator in charge of providing DR services in the MG, by controlling the collective controllable loads. Two types of controllable load resources are considered in this paper: curtailable loads and time-shiftable loads.

- *Curtailable loads:* At certain times, some percentage of the total demand is available for curtailment. The curtailment process can cause discomfort to the users and is to be minimized. Hence, a concave utility function (\mathbf{U}_2^1) is defined to penalize deviation from the desired consumption schedule. An exponential utility function is adopted here based on [60].

$$\mathbf{U}_2^1 = \frac{1}{H} \cdot \sum_{t=1}^H \{\lambda_G(t) \cdot P_f(t) \cdot (1 - e^{-\omega(P_f(t) - P_C(t))})\} \quad (5.9)$$

$$\mathbf{P}_C^{min} \leq \mathbf{P}_C(t) \leq \mathbf{P}_C^{max} \quad (5.10)$$

where, constraint (5.10) defines the boundaries of the aggregate curtailable load power (\mathbf{P}_C), which is between its minimum and maximum values (i.e., $[\mathbf{P}_C^{min}, \mathbf{P}_C^{max}]$).

- *Time-shiftable loads:* This type of DR resource is composed of the aggregation of loads that need to consume a certain amount of energy within a certain time frame $[t_{min}, t_{max}]$ (e.g., electric vehicles' charging load). Hence, such loads cannot be employed sooner than t_{min} or later than t_{max} . Similar to curtailable loads, a concave utility function (U_2^2) is defined for time-shiftable load power (P_{TS}) to penalize deviations from the pre-defined customer schedule (P_{Sch}):

$$U_2^2 = \sum_{t=1}^H \{-(P_{TS}(t) - P_{Sch}(t))^2\} \quad (5.11)$$

$$P_{TS}^{min} \leq P_{TS}(t) \leq P_{TS}^{max}, \forall t \in [t_{min}, t_{max}] \quad (5.12)$$

$$\sum_{t=t_{min}}^{t_{max}} P_{TS}(t) \cdot \Delta t = \sum_{t=t_{min}}^{t_{max}} P_{Sch}(t) \cdot \Delta t = E_{Sch} \quad (5.13)$$

while (5.12) enforces the maximum/minimum limits of time-shiftable DR resource, (5.13) maintains and preserves the total scheduled energy consumption (E_{Sch}). Note that these constraints also guarantee that the time-shiftable resources are employed within the $[t_{min}, t_{max}]$ interval.

Cost saving is considered to be the third objective function of the DRP, denoted as U_2^3 :

$$U_2^3 = \sum_{t=1}^H \{P_{TS}(t)\lambda_G(t) - P_C(t)\lambda_G(t)\} \quad (5.14)$$

4. **PCC link:** To prevent overloading in the link that connects the MG with the main grid at the PCC and defer distribution system expansion/upgrades, the following objective function (adopted from [174]) and the corresponding

constraint are used:

$$U_3^1 = \sum_{t=1}^H \{-(P_G(t))^2\} \quad (5.15)$$

$$P_G^{min} \leq P_G(t) \leq P_G^{max} \quad (5.16)$$

where, P_G^{min} and P_G^{max} denote the limits for power export and import to/from the main grid, respectively. The idea behind objective function (5.15) is to promote self-sufficiency of the MG and reduce the reliance on the grid, while maintaining a safe margin to avoid congestion/overloading. Note that while constraint (5.16) enforces the physical congestion/overloading boundary at the PCC, it is not necessarily able to create a desired safe congestion margin. Another approach to this problem is to eliminate objective function (5.15) and tighten the constraint (5.16).

5. **PV and fixed load:** The renewable PV power (P_R) and the fixed load power (P_f) are assumed to be non-dispatchable at all times. These powers, as explained in the previous subsection, are simply predicted (with a certain forecast error). While the PV power does not appear as decision variable in the power management problem, it is controlled at the lower level of the hierarchy using maximum power point tracking.

Apart from the private constraints of different resources discussed above, the global MG-wide power balance constraint, which connects the output power of all the power sources in the system, should also be respected at all times:

$$P_{DG}(t) + P_R(t) + P_{ESS}(t) + P_G(t) + P_C(t) = P_f(t) + P_{TS}(t) \quad (5.17)$$

Hence, the MOPM problem for the MG can be written as follows:

$$\begin{aligned} & \max_{\mathbf{P}} \{U_1^1, U_1^2, U_2^1, U_2^2, U_2^3, U_3^1\}, \\ & \text{s.t. (5.4), (5.5), (5.6), (5.7), (5.8), (5.10), (5.12), (5.13), (5.16), (5.17)} \end{aligned} \quad (5.18)$$

where, \mathbf{P} is the vector of decision variables, consisting of the power of controllable microsources within the MG (including the exchanged power with the main grid) for the look-ahead time in which the power management problem is solved:

$$\begin{aligned} \mathbf{P} = & [P_{DG}(1), \dots, P_{DG}(H), P_{ESS}(1), \dots, P_{ESS}(H), \\ & P_G(1), \dots, P_G(H), P_C(1), \dots, P_C(H), P_{TS}(1), \dots, P_{TS}(H)]^T \end{aligned} \quad (5.19)$$

where, $[\cdot]^T$ denotes vector transpose operation. In this paper vector quantities are indicated via bold letters. We also define M to be the number of elements of the decision vector \mathbf{P} for future use (i.e., $\mathbf{P} \in \mathbb{R}^M$). Note that in the optimization problem (5.18), all the objective functions are concave in the decision variable and the constraints form convex sets. Hence, the overall MOPM problem is convex, which implies that the Pareto-front defines the boundary of a convex set [44]. As will be discussed in the next section, convexity of the power management problem is crucial for the NBS to be well-defined. To solve this optimization problem a distributed agent-based bargaining framework is designed.

Agent-Based Distributed Bargaining Framework

In this section, first we formulate the MOPM problem as a bargaining game. Then a distributed optimization technique is employed to find the solution to the game.

NBS as a Solution Concept

A bargaining game is used to model a situation of interactive cooperative resource allocation among several agents. Hence, bargaining games consist of the following elements [132]:

- A set of N players (agents), $\mathbf{Ag} = \{1, \dots, N\}$ that negotiate with each other to find a globally agreeable solution.
- A set of utility or pay-off functions, $\mathbf{U} = \{\mathbf{u}_1, \dots, \mathbf{u}_N\}$, where \mathbf{u}_i denotes the i^{th} player's pay-off level at each state of the bargaining game. The goal of each agent is to maximize its pay-off function through negotiations with its peers.
- A set of disagreement points, $\mathbf{D} = \{\mathbf{d}_1, \dots, \mathbf{d}_N\}$, where \mathbf{d}_i denotes the worst case pay-off value for the i^{th} player if the negotiations break down. Hence, the disagreement points represent the tacit threat of inability of agents to reach an agreement. If the bargaining game is well-defined (i.e., the disagreement points have worse performance than every other solution) and the agents are “rational” then the disagreement point is never reached.

The Pareto-front of the pay-off functions of the players constitute the set of all the rational solutions that the agents can reach through negotiations. Given that the Pareto-front is the optimal trade-off set of the pay-off space of the agents, any deviation from this set would be detrimental to at least one agent. In other words, the Pareto-front of the game determines the set of equilibria to the bargaining situation. NBS was proposed to define a single unique solution (among the candidates on the Pareto-front) to the bargaining game. The properties of NBS are as follows [132]:

- NBS can be obtained using optimization problem (5.20). This optimization problem is solved over the feasible solution set within the pay-off space of the

players (F_U).

$$NBS = \arg \max_{(u_1, \dots, u_N) \in F_U} \prod_{i=1}^N (u_i - d_i). \quad (5.20)$$

Optimization problem (5.20) can be formulated as follows:

$$NBS = \arg \max_{(u_1, \dots, u_N) \in F_U} \sum_{i=1}^N \log(u_i - d_i). \quad (5.21)$$

Compared to (5.20), (5.21) is much more beneficial for our purpose, as will become clear in the next subsection.

- **Uniqueness:** If F_U is a convex set (i.e., the bargaining game is convex) then (5.21) is a convex optimization problem and NBS is the global optimum to the problem and is unique.
- **Efficiency (Pareto-optimality):** Given a convex bargaining game, NBS (obtained through (5.21)) is guaranteed to be Pareto-optimal (i.e., NBS lies on the Pareto-front of the bargaining game).
- **Fairness:** If the bargaining game is symmetric with respect to players i and j (i.e., if $(u_i = u, u_j = u') \in F_U$ then $(u_i = u', u_j = u) \in F_U$), then those players will receive the same pay-off value with NBS. This means that NBS does not discriminate between identical players and the outcome of the bargaining is guaranteed to be fair under NBS.
- **Covariance under positive affine transformation:** NBS is independent of unit of measurement of the pay-off functions of the players. Also, multiplying the objective functions by scalars does not change the outcome of the bargaining.
- **Independence of irrelevant alternatives:** NBS is insensitive to changes in the set of inferior alternative solutions.

Since in both MO optimization problem and bargaining game the goal is to reach a solution on the Pareto-front of the problem, the MOPM problem (5.18) can be thought of as a bargaining game, with each agent having different sets of objective functions. Since (5.18) is a convex optimization problem, NBS can be applied to find a unique, fair, and Pareto-optimal solution for the power management problem. Given (5.21), the NBS-based power management problem is formulated as follows:

$$\begin{aligned} & \max_{\mathbf{P}} \left\{ \sum_{i=1}^N \log \left(\prod_{j=1}^{O_i} (U_i^j - d_i^j) \right) \right\}, \\ & \text{s.t. (5.4), (5.5), (5.6), (5.7), (5.8), (5.10), (5.12), (5.13), (5.16), (5.17)} \end{aligned} \quad (5.22)$$

where, O_i denotes the number of objective functions considered for the i^{th} agent. Note that optimization problem (5.22) is also convex and has a unique globally optimal solution, which defines the NBS to the bargaining among the agents.

Distributed Optimization Approach

Our goal in this paper is to solve (5.22) using an agent-based framework. This optimization problem is an instant of DSO problems. The general structure of DSO problems is as follows:

$$\begin{aligned} & \min_{\mathbf{x}_1, \dots, \mathbf{x}_N} \left\{ \sum_{i=1}^N f_i(\mathbf{x}_i) \right\}, \\ & \text{s.t. } \mathbf{x}_i \in X_i \end{aligned} \quad (5.23)$$

where, \mathbf{x}_i and f_i denote the decision vector and the convex objective function of i^{th} agent, respectively. Also, X_i defines the convex feasible region of vector \mathbf{x}_i . Note that in general, feasible regions and decision vectors of different agents can have

overlapping areas and common elements.

Problems of the form (5.23) can be solved using distributed optimization algorithms without the need for a central solver. In a distributed optimization framework, the agents exchange their estimation of the solution of (5.23) with each other using a communication network, without sharing their sensitive private cost and feasibility data (i.e., \mathbf{f}_i and \mathbf{X}_i) with their peers. In this paper, we have employed the DGA to solve (5.22) in a distributed manner. The DGA consists of three main steps that are performed at each iteration of the algorithm:

- **Step I:** at the \mathbf{k}^{th} iteration of the algorithm, the i^{th} agent performs a weighted averaging operation (with weights \mathbf{a}_i^j) over the received signals from its neighboring agents (i.e., including its own estimated solution):

$$\boldsymbol{\omega}_i(\mathbf{k}) = \sum_{j=1}^{N_i} \mathbf{a}_i^j \mathbf{x}_j(\mathbf{k}) \quad (5.24)$$

where, N_i denotes the i^{th} agent's number of neighboring agents (including the i^{th} agent). In this paper, a uniform weighting mechanism is selected for the distributed optimization model (i.e., $\mathbf{a}_i^j = \frac{1}{N_i}$). Any weighting mechanism that satisfies the double-stochasticity property (i.e., $\sum_{j=1}^{N_i} \mathbf{a}_i^j = \mathbf{1}$ and $\sum_{i=1}^N \mathbf{a}_i^j = \mathbf{1}$) guarantees the convergence of the algorithm [149]. A uniform weighting scheme not only satisfies double-stochasticity, but is also intuitive and easy to implement.

- **Step II:** at this step, each agent performs a gradient descent operation, as follows:

$$\mathbf{v}_i(\mathbf{k}) = \boldsymbol{\omega}_i(\mathbf{k}) - \alpha_k \cdot \nabla_{\mathbf{x}_i} f_i(\mathbf{x}_i(\mathbf{k})) \quad (5.25)$$

where, α_k is a time-varying weight factor and is selected as $\alpha_k = \frac{\gamma}{k+1}$, with γ

acting as a tunnable parameter of the model.

- **Step III:** each agent projects the outcome of Step II into its private feasible region to update its estimated solution for the next iteration:

$$\mathbf{x}_i(\mathbf{k} + \mathbf{1}) = \Pi_{X_i}\{\mathbf{v}_i(\mathbf{k})\} \quad (5.26)$$

where, Π_{X_i} defines the projection operation into the set X_i . Note that the projection operation is a convex quadratic programming [26], which is determined as follows:

$$\begin{aligned} \Pi_{X_i}\{\mathbf{v}_i(\mathbf{k})\} &= \arg \min_{\mathbf{y}} \|\mathbf{y} - \mathbf{v}_i(\mathbf{k})\| \\ &s.t. \mathbf{y} \in X_i \end{aligned} \quad (5.27)$$

where, $\|\cdot\|$ is the Euclidean norm.

Mathematical properties of the DGA, including the guarantees of convergence, are discussed in [149] and [150] in details, and we refrain from discussing these properties here. However, an interesting practical property of the DGA is that even for time-varying communication networks (e.g., when some communication links are lost temporarily) it is guaranteed to reach the optimal solution, as long as each agent is able to affect every other agent's estimation (directly or indirectly), infinitely often [149].

To apply the DGA to the NBS-based power management problem, we compare (5.23) and (5.22), and note that the following holds for each microsource agent in the MG:

$$\mathbf{f}_i(\mathbf{P}) = -\log\left(\prod_{j=1}^{O_i} (U_i^j - d_i^j)\right). \quad (5.28)$$

It can be shown that the gradient of $f_i(\mathbf{P})$ with respect to the vector of decision variables (i.e., \mathbf{P}) can be obtained for each agent, as follows:

$$\nabla_{\mathbf{P}} f_i(\mathbf{P}) = - \begin{bmatrix} \frac{\partial U_i^1}{\partial P_1} & \cdots & \frac{\partial U_i^{O_i}}{\partial P_1} \\ \vdots & \ddots & \vdots \\ \frac{\partial U_i^1}{\partial P_M} & \cdots & \frac{\partial U_i^{O_i}}{\partial P_M} \end{bmatrix} \begin{bmatrix} \frac{1}{U_i^1 - d_i^1} \\ \vdots \\ \frac{1}{U_i^{O_i} - d_i^{O_i}} \end{bmatrix} \quad (5.29)$$

where, the first term on the right side of (5.29) is a sensitivity matrix, which is equal to the transpose of the Jacobian matrix of the vector function $\mathbf{U}_i(\mathbf{P}) = [U_i^1(\mathbf{P}) \dots U_i^{O_i}(\mathbf{P})]^T$. The second term in (5.29) is a vector which embodies the effect of disagreement points of the bargaining. Basically, its function is to push the decision variables away from the disagreement region that represents the worst case outcome of the bargaining. Equation (5.29) is substituted in (5.25) to complete the distributed bargaining framework for the MG. To guarantee the convergence of the DGA to the optimal solution, the gradient of the global objective function of the optimization problem needs to be defined and finite inside the feasible decision region of the agents [149] [150]. In order to achieve this, in practice the disagreement points of the agents need to be placed outside (but close to) the feasible region of the decision problem to avoid singular gradient values.

The agents participating in the bargaining process, their objective function sets, and feasible regions are as follows:

1. DG agent: $\mathbf{U}_1 = [U_1^1 \ U_1^2]^T$ and $\mathbf{X}_1 = \{(5.4) \cap (5.5) \cap (5.17)\}$.
2. DRP agent: $\mathbf{U}_2 = [U_2^1 \ U_2^2 \ U_2^3]^T$ and $\mathbf{X}_2 = \{(5.10) \cap (5.12) \cap (5.13) \cap (5.17)\}$.
3. PCC agent: $\mathbf{U}_3 = [U_3^1]^T$ and $\mathbf{X}_3 = \{(5.16) \cap (5.17)\}$.

4. ESS agent: $\mathbf{U}_4 = [0]^T$ and $\mathbf{X}_4 = \{(5.6) \cap (5.7) \cap (5.8) \cap (5.17)\}$.

To summarize, NBS has the following advantages compared to conventional power management approaches: uniqueness, fairness, Pareto-optimality, and the capability to be obtained through a distributed optimization framework.

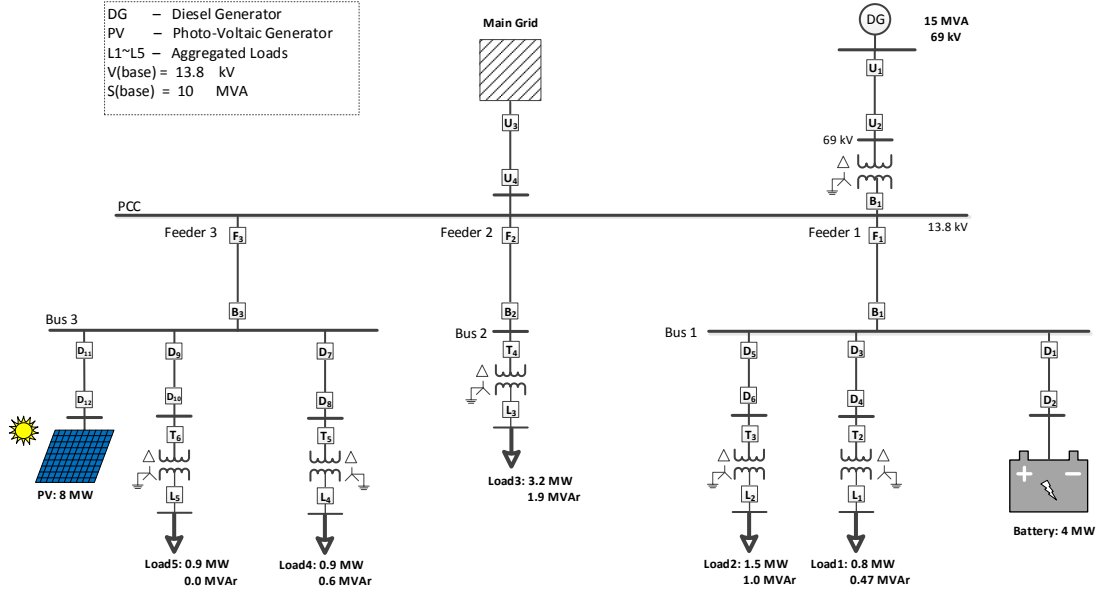


Figure 5.2: Modified IEEE 13-bus standard system, as a grid-connected MG

Numerical Experiments and Results

The proposed MO bargaining framework is tested on two distinct MGs: 1) a generic islanded MG (Fig. 5.1), and 2) a modified version of IEEE standard 13-bus distribution network, as a grid-connected MG, including a solar PV farm (Fig. 5.2). The detailed system and microsource data for these two MGs can be found in [167] and [168], respectively. The fixed load data and the PV power output used in the simulations are adopted from [110], and [59], respectively. The non-controllable fixed load profile and the PV power output for the 13-bus system are shown in Fig. 5.3 and

Fig. 5.4 (similar curves can be drawn for the islanded MG). Note that, as discussed before, these two curves act as inputs to the model and need to be forecasted for the decision horizon. In this paper we have used a time step of 5 minutes ($\Delta t = 5 \text{ min}$) and a look-ahead decision horizon of 4 hours ($T = 4 \text{ hours}$ and $H = 48$). The simulation results are obtained under fixed and time-varying (ToU) pricing scenarios.

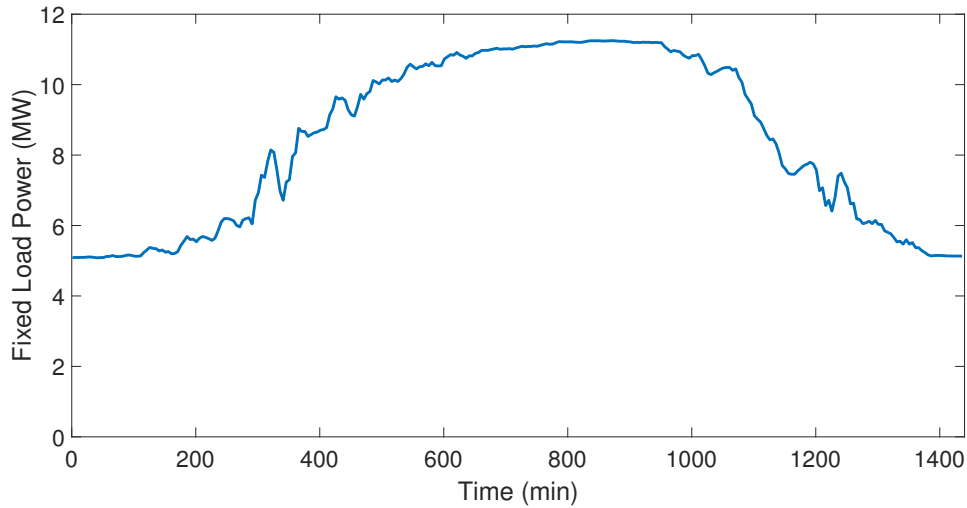


Figure 5.3: Uncontrollable fixed load profile

Case I: Islanded MG

To verify the results of the proposed distributed bargaining framework, the optimization problem (5.22) has also been solved using a central optimization method on a generic islanded MG (shown in Fig. 5.1). It was observed that both the distributed optimization framework and the central solver yielded the same results, which confirms the validity of the proposed methodology.

To show that the NBS of the MOPM lies on the Pareto-front of the objective space, we have obtained the Pareto-front of the power management problem of the

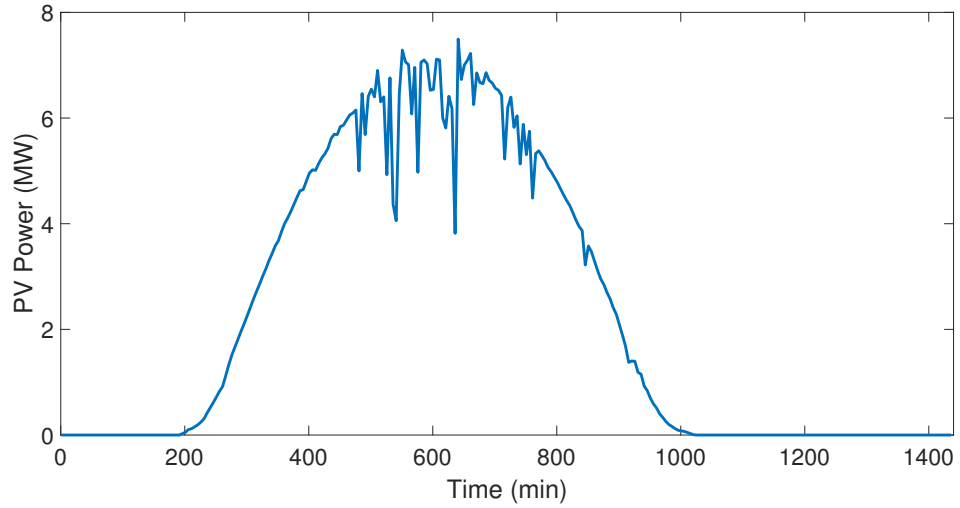


Figure 5.4: Output power of PV power generator

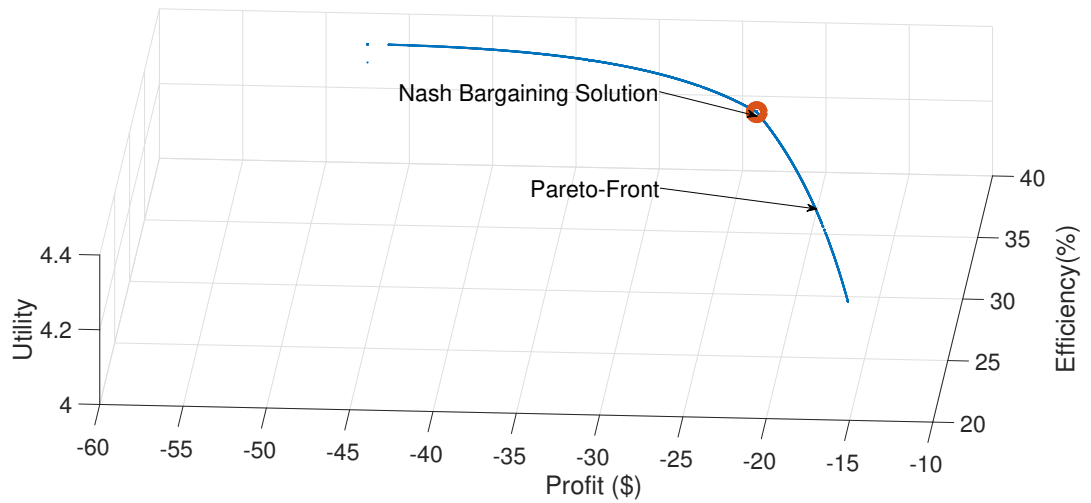


Figure 5.5: The Pareto-front and the NBS

islanded MG, using a central weighted-sum optimization approach [44]. The problem description for the central weighted-sum optimization to obtain the Pareto-front is as follows:

$$\begin{aligned} \max_{\mathbf{P}} \{ & \sum_{i=1}^N \sum_{j=1}^{O_i} \gamma_i^j \cdot U_i^j \}, \\ \sum_{i=1}^N \sum_{j=1}^{O_i} \gamma_i^j &= \mathbf{1}, \quad \mathbf{0} \leq \gamma_i^j \leq \mathbf{1}, \end{aligned} \quad (5.30)$$

s.t. (5.4), (5.5), (5.6), (5.7), (5.8), (5.10), (5.12), (5.13), (5.16), (5.17)

where, the weights γ_i^j are varied to track the Pareto-front of the MO problem. Since this problem is convex then by solving the central optimization (5.30) the entire Pareto-front can be mapped [44].

In this case, three objectives are considered to be able to show the Pareto-front on a graph (Fig. 5.5). These objectives are: DG efficiency, curtailable DR utility, and profit (which in an islanded system turns into the negative of cost of production). The NBS of the power management problem is also obtained using the proposed distributed optimization framework and shown on the same figure. As can be seen in Fig. 5.5, the NBS (obtained through distributed optimization) is correctly located on the Pareto-front of the power management problem (obtained using a central optimization technique), as was expected. This confirms that the distributed optimization framework converges to a solution on the Pareto-front of the MOPM problem. This solution, as discussed before, is the NBS of the bargaining game. We have used Case I as a result verification tool.

Case II: Grid-Connected MG

In this section, we present the results of the simulations on the grid-connected MG, shown in Fig. 5.2. All the six objective functions considered in Section II are taken into account. The unit price of exchanged energy with the main grid (fixed and ToU pricing) are shown in Fig. 5.6.

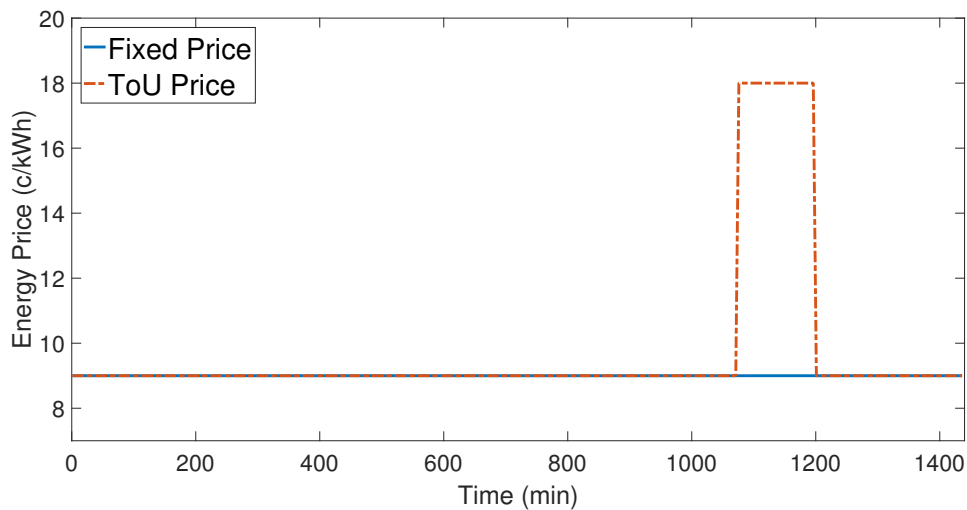


Figure 5.6: Main grid energy price

In Fig.5.7, the output power of the thermal DG unit is shown. As can be seen, the output power of the DG is almost the same under both of the pricing scenarios. Also, due to the introduced ramp rate constraint (5.5) the DG needs to start increasing its output power at an earlier time to be able to respond to the peak load, at the later time of the day. On the other hand, the effect of variable energy pricing is notably observed in the behavior of time-shiftable DR resources, shown in Fig. 5.8. As can be seen in this figure, compared to the fixed pricing scenario (original scheduled profile), under ToU pricing the time-shiftable DR resources are deployed in a way to eliminate consumption during peak-price time period and reduce the cost of consumption (note that under both pricing scenarios the same amount of energy is consumed in a pre-

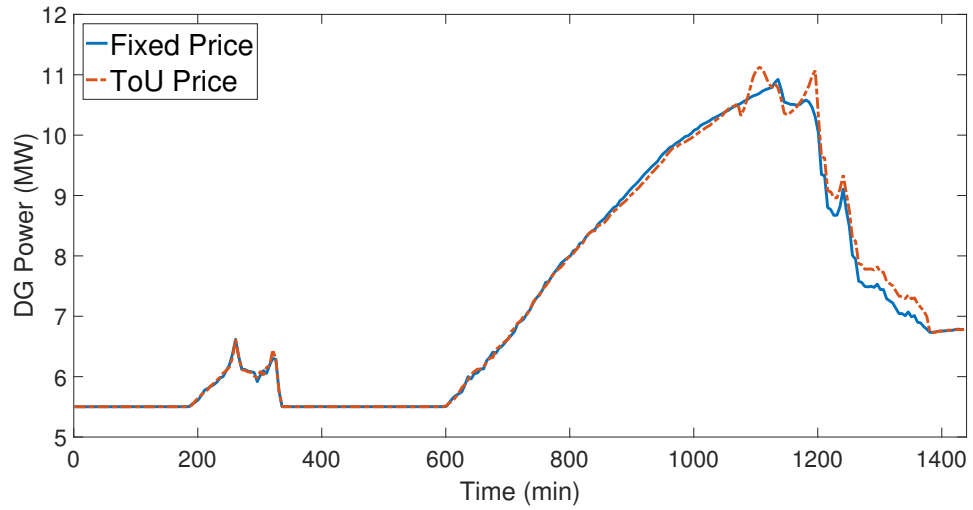


Figure 5.7: DG output power

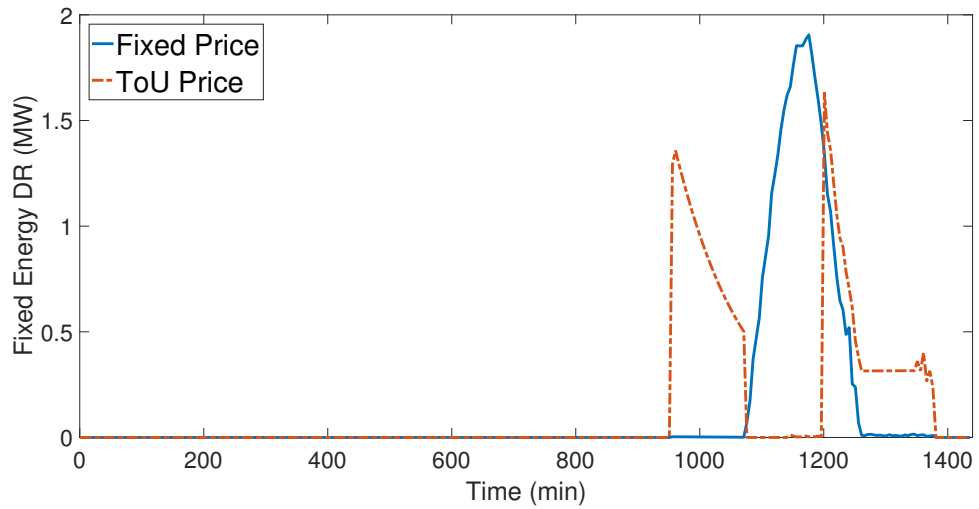


Figure 5.8: Time-shiftable DR resource profiles

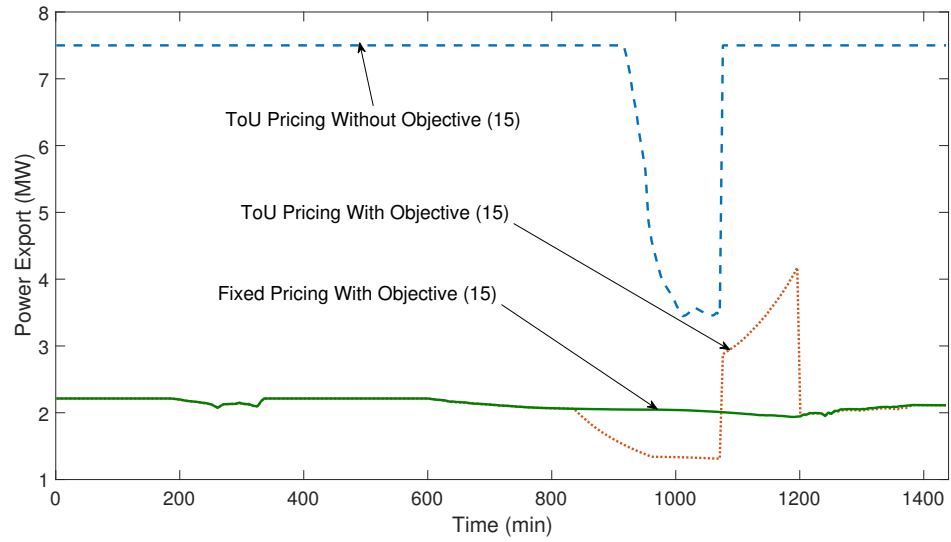


Figure 5.9: Exchanged power with the grid

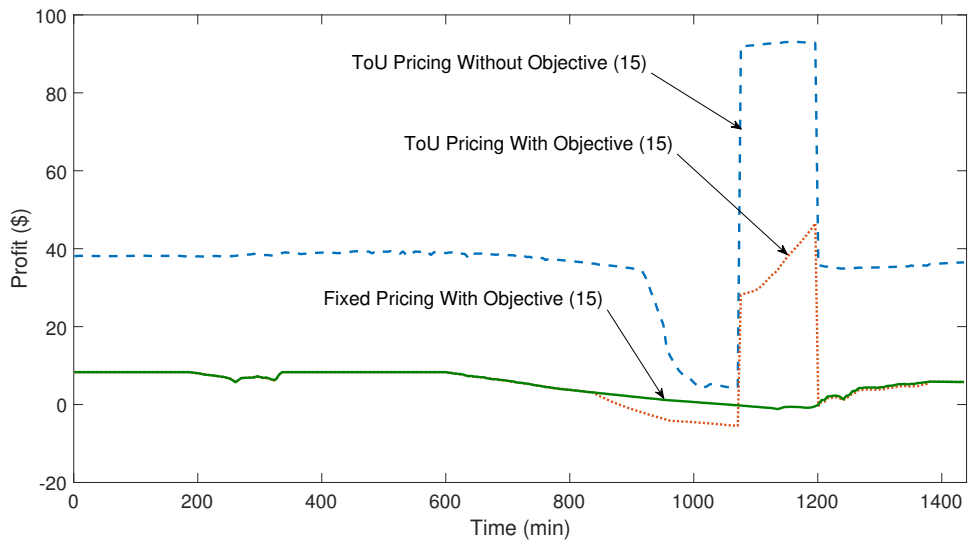


Figure 5.10: Profit profile of the MG

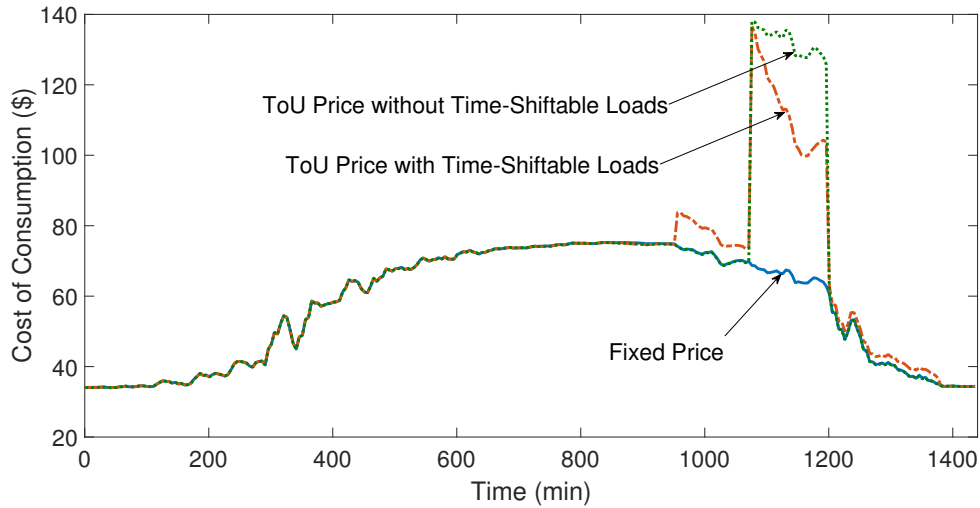


Figure 5.11: Total cost of power consumption

defined time frame). The original available power value of time-shiftable loads is shown in the figure under fixed price scenario. These resources are available from time 18:00 to 21:00, and can be shifted within the time interval 16:00 to 23:00 (i.e., they cannot be consumed before 16:00 or after 23:00). Since in the fixed price scenario the time-shiftable loads cannot achieve any cost savings by shifting their consumption (due to the fixed price), no load shifting is performed and the consumers fulfill their original schedule (which has a peak of around 2 MW, used as an input to the decision model).

The effect of time-shiftable load can be observed in the power exchange with the main grid, shown in Fig. 5.9. As can be seen in this figure, due to the load-shifting process, the amount of power export to the main grid is increased considerably during the peak-price period, to gain more profit from the sale of energy. This comes at the expense of lower power export at earlier times. Note that because of the objective function (5.15), the exported power is limited to 4.2 MW (Fig. 5.9) and does not reach its congestion limit of 7.5 MW. However, when objective function (5.15) is

removed the exported power to the grid is set to its maximum feasible value of 7.5 MW for most of the time (except for a short period before price peak interval, where time-shiftable loads create an increase in power consumption which leads to less power export).

The profit curve of the MG is shown in Fig. 5.10, where we observe a 47% increase in the total profit level of the MG, under ToU pricing with time-shiftable DR resources. Also, compared to the case of ToU pricing without time-shiftable DR resources, the total profit level shows 17.6% improvement. Without objective function (5.15), higher export levels lead to considerably higher profit, as shown in the figure. However, this comes at the expense of high power utilization and congestion of the line at the PCC. Since line congestion on the lines signal the need for network expansion/upgrade, by using objective function (5.15) we are creating a balance between the two objectives: short-term profit and avoiding the need for long-term expansion of distribution system.

The total cost of power consumption is shown in Fig. 5.11. As can be seen in this figure, the cost of consumption increases at the times where the energy price is higher. However, the total cost of consumption is reduced by 44% when time-shiftable loads are present, compared to the case without time-shiftable loads.

The power and stored energy of the battery system are depicted in Fig. 5.12 and Fig. 5.13, respectively (with negative power values indicating battery charging). As is observed in these figures the volatility and variations of the renewable PV power is absorbed by the storage system. Hence, from the perspective of the main grid, the volatility of the PV power does not affect the grid (note the smooth power curve of Fig. 5.9). This implies that employing the proposed MG-based power management procedure, the undesired effects of volatility of distributed renewable resources can be limited, which leads to the successful integration of these resources into the electrical

energy networks. Also, it can be observed from Fig. 5.13 that the stored energy of the battery is correctly kept between its maximum and minimum limits corresponding to $SOC^{max} = 0.9$, and $SOC^{min} = 0.3$, respectively.

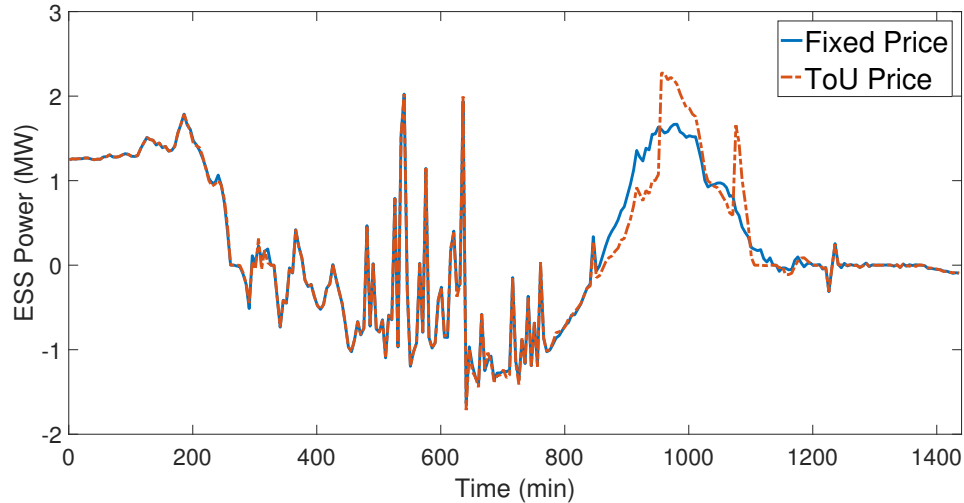


Figure 5.12: Battery storage output power

In Fig. 5.14, the maximum available power profile of curtailable DR resources and the portion used in our proposed method are shown (for $\omega = 3$). The maximum available curtailable load is assumed to be equal to 20% of total fixed load at all times. The percentage of the DR employed under our proposed method (for both ToU and fixed price scenarios) is only 50% of the maximum available curtailable DR resources.

Conclusion

In this paper a bargaining framework was proposed to solve the MOPM problem of MGs. The proposed framework employs NBS to find a unique and fair solution on the Pareto-front of the optimization problem. Moreover, the solution is obtained using a distributed optimization method which relies on an agent-based decision

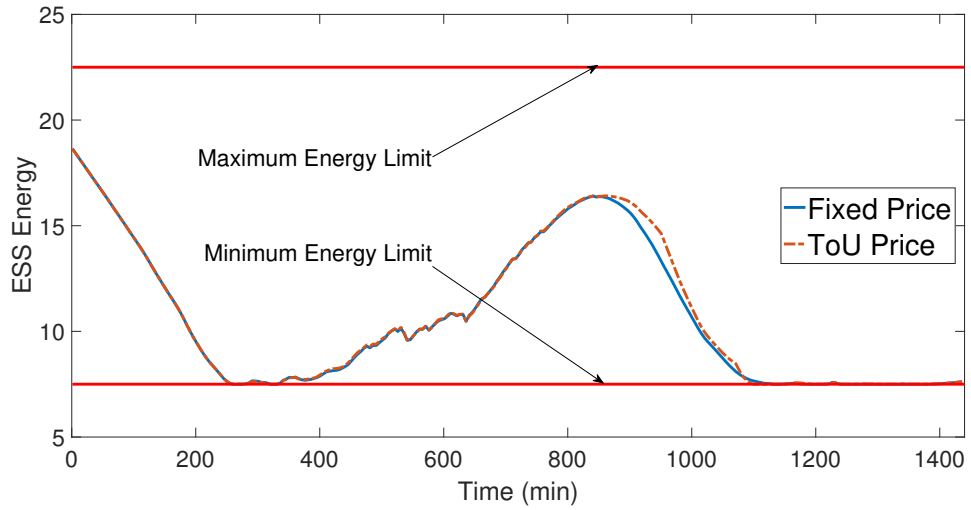


Figure 5.13: Stored energy profile of the battery system

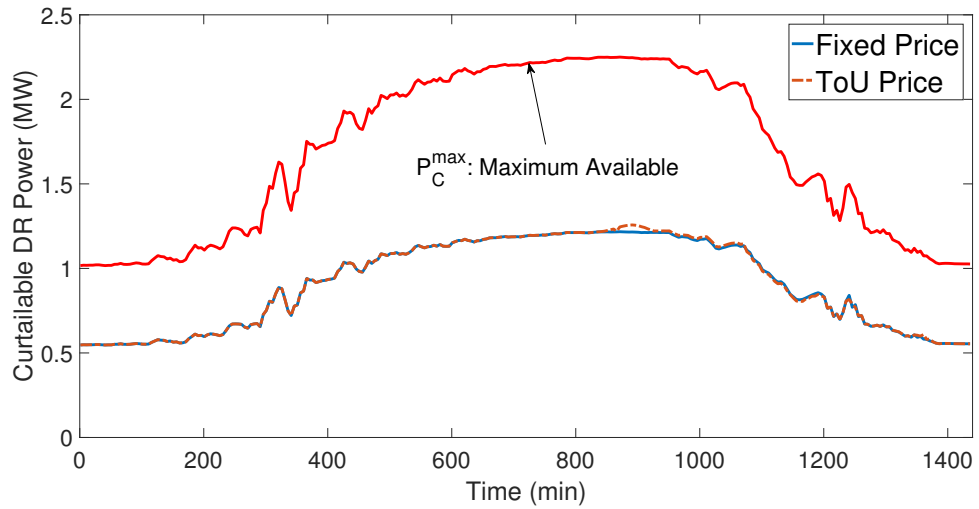


Figure 5.14: Curtailable DR power profile

architecture. It is shown that using the proposed methodology the MOPM problem can be solved in islanded and grid-connected MGs with various types of microsources, including DGs, renewable power generators, ESS units, and curtailable and time-shiftable loads.

AN AGENT-BASED HIERARCHICAL BARGAINING FRAMEWORK FOR
POWER MANAGEMENT OF MULTIPLE COOPERATIVE MICROGRIDS

Contribution of Authors and Co-Authors

Manuscript in Chapter 6

Author: Kaveh Dehghanpour

Contributions: Developed and tested the distributed bargaining framework for microgrid control in the retail market hierarchy, and prepared the manuscript.

Co-Author: Hashem Nehrir

Contributions: Supervised the overall flow of the project, and provided important insight on numerical studies and interpretation of the results. Aided in the preparation of the manuscript.

Manuscript Information Page

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Abstract

In this paper, we propose an agent-based hierarchical power management model in a power distribution system composed of several MicroGrids (MGs). At the lower level of the model, multiple MGs bargain with each other to cooperatively obtain a fair, and Pareto-optimal solution to their power management problem, employing the concept of Nash Bargaining Solution (NBS) and using a distributed optimization framework. At the highest level of the model, a distribution system power supplier, e.g. a utility company, interacts with both the cluster of the MGs and the wholesale market. The goal of the utility company is to facilitate power exchange between the regional distribution network consisting of multiple MGs and the wholesale market to achieve its own private goals. The power exchange is controlled through dynamic energy pricing at the distribution level, at the day-ahead and real-time stages. To implement energy pricing at the utility company level, an iterative machine learning mechanism is employed, where the utility company develops a price-sensitivity model of the aggregate response of the MGs to the retail price signal through a learning process. This learned model is then used to perform optimal energy pricing. To verify its applicability, the proposed decision model is tested on a system with multiple MGs, with each MG having different load/generation data.

Introduction

MicroGrids (MGs), as small-scale self-sustainable energy units, represent an attractive opportunity for large-scale integration of renewable and non-renewable micro-sources into power distribution systems. However, as the number of MGs in Regional Energy Networks (RENs) grows, developing control and power management logics to coordinate the operation of MGs and facilitate their constructive interaction

becomes crucial. Also, it is critical to design retail market mechanisms considering the autonomy of MGs in the regional distribution networks. Noting that MGs introduce higher levels of controllability and price-aware functionalities into the system, the effect of their increasing penetration on retail market operation will no longer be negligible.

Several papers have addressed different aspects of the problem of controlling and energy management of power systems with multiple MGs. In [230], a frequency reserve provision procedure is proposed using a market mechanism including several MGs. Different control strategies are examined in order to enable the participation of renewable resources in frequency control. In [153] and [154], using auction theory a two-level market framework is developed to facilitate power trading among multiple MGs. The proposed auctions are based on control agents that participate in local and global markets through bidding. In [131], another bi-level decision hierarchy is proposed. At the local level total cost minimization for each MG is addressed, while at the upper level a central control unit is in charge of coordinating multiple MGs to balance power and prevent excess/shortage of power at the global level. In [201], charging management of electric vehicles in a multi-MG environment is studied using a decentralized price-based strategy. In [202], the problem of cooperation among several MGs using a hierarchical scheduling approach, exploiting MG diversity gain to optimize performance and user satisfaction is addressed. In [111], using Stackelberg game model, a distributed framework is proposed to design trading processes among several MGs. In [71], a distributed-optimization-based model is proposed with the objective of minimizing the total operational cost of multiple MGs.

This paper is the extension of our earlier work, [45], where we extend the agent-based model for Multi-Objective (MO) power management for one MG to a multi-MG system. The basic idea here is to design an MG-wide distributed bargaining

framework, using Nash Bargaining Solution (NBS) [132], to obtain a fair and Pareto-optimal solution to the power management problem. We have employed a distributed optimization approach (using the Distributed Sub-Gradient Algorithm (DSGA) [149] [150]) to implement a networked decision system. Hence, a multi-MG-system-wide MO optimization problem is solved through a distributed optimization model. The proposed model consists of three levels, as shown in Fig. 6.1. At the lowest level, the control agents of the micro-sources within each MG interact with each other to pursue the MG-wide objectives while satisfying the MG-wide constraints. At the upper level, the main control agents of the MGs at the Point of Common Coupling (PCC) interact with each other (and with the lower level control agents of the micro-sources of their own MG) to satisfy the multi-MG-level constraint of power balance. The upper level communication structure is sparser than the lower level interaction topology due to lower number of agents involved, as demonstrated in Fig. 6.1. This sparsity implies lower communication overhead which also permits data-privacy and data-ownership at individual MG level. While the lower level agents do not participate in the upper level bargaining process directly, the outcome of the lower level process is affected by the upper level negotiations. DSGA is employed to implement these two levels of distributed bargaining. Given that the concept of NBS is adopted from the area of cooperative game theory [132], the cluster of MGs act as a cooperative community of players trying to reach a fair and optimal resource allocation. At the third and the highest level of the model, a power utility company acts as a retail market agent for the cluster of the MGs. The utility company facilitates power exchange between the distribution system and the wholesale market, by setting the retail energy price for the MGs. Hence, a dynamic pricing mechanism is adopted by the utility company to pursue its own objectives. Basically, the goal of the utility company is to indirectly control the outcome of the lower-level bargaining process to its own benefit.

The dynamic pricing procedure is based on our previous work in [48]. However, in [48] only a specific type of residential load was considered for the Day-Ahead (DA) retail market. In this paper, we expand the pricing model of [48] to include more active micro-sources at both the DA and Real-Time (RT) retail markets. At the DA stage the objective of the utility company is to maximize its profit based on the forecasted state of the system, subject to certain constraints, employing DA retail pricing. However, as we get closer to RT operation of the system, due to variations in system states (e.g., forecast errors, RT islanding scenarios, system failure) deviations from the DA schedule can occur. In this paper, we assume that at the RT stage the objective of the utility company is to minimize these deviations through RT retail pricing (i.e., any mismatch between the DA and RT power schedules are penalized in the regulation market.) Hence, the utility company's learned model is embedded within its DA and RT optimization problems to obtain the optimal retail price signals at those stages. Given the distributed, bi-directional and price-based nature of the decision model, we can argue that the overall methodology falls under the category of transactive control [106].

In summary, the main contributions of the paper are as follows:

- Employing the concept of NBS to address the cooperative and MO nature of the problem of resource allocation among multiple MGs. The NBS is cooperatively obtained by the MGs using a distributed optimization method (DSGA) without the need for a central controller. Hence, the MG agents are able to reach a consensus at any given retail price without the need for a central coordinator.
- The decision model at the MG level (excluding the utility company) is decomposed into two sub-layers to obtain a sparse communication network and reduce the communication overhead (the overall interaction architecture of the

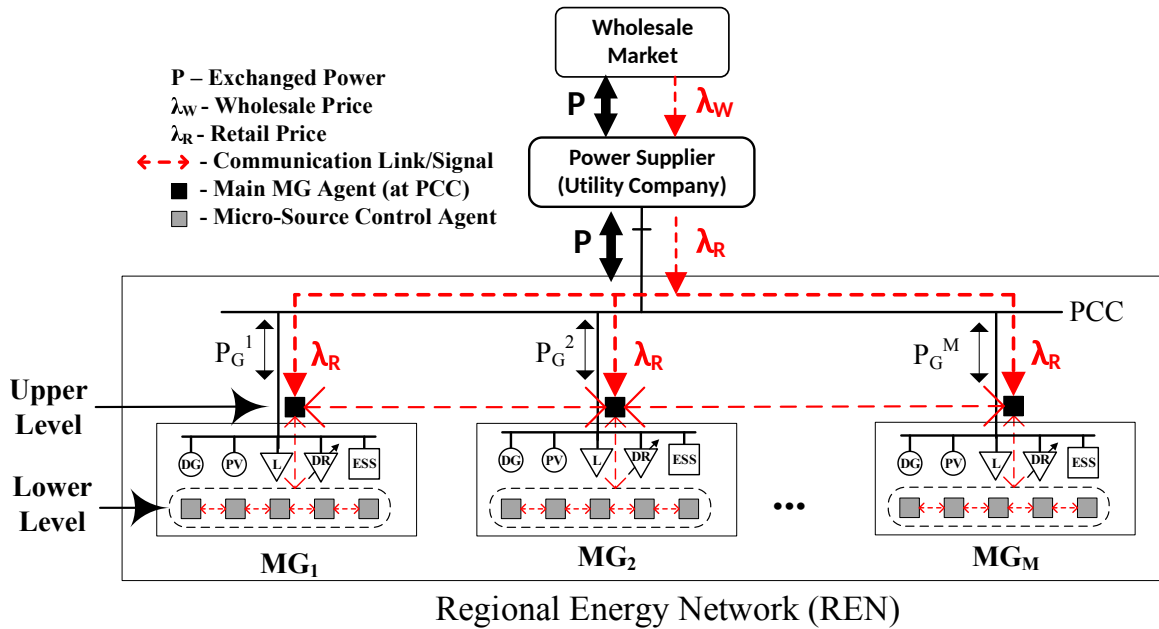


Figure 6.1: Interaction structure of the proposed model

model is shown in Fig. 6.1)

- At the highest level (i.e., third level), a novel iterative retail pricing mechanism is introduced to be used by a utility company, based on a machine learning approach. Retail prices are obtained at different time stages (DA and RT) using a model learning procedure, through which the utility company estimates the price-responsivity of the MGs without having direct access to their decision model and private data.

The rest of the paper is constructed as follows: in Section II the overall structure of the MO distributed bargaining framework for the cluster of cooperative MGs is discussed. The decision problem of the utility company and its solution technique are presented in Section III. The results of the numerical experiments are shown and discussed in Section IV. The conclusions of the paper are presented in Section V.

Multi-MG Distributed Bargaining

In this section, the MO distributed bargaining mechanism (defining the first two levels of the decision model) is discussed. A rolling horizon optimization scheme, [19], is employed in RT to solve the distributed optimization problem. In this scheme, at each time instant (\mathbf{t}) the power management problem is solved for a certain look-ahead time ($\mathbf{t} + \mathbf{T}$), based on the realized and forecasted values for renewable energy resources and the load, where \mathbf{T} denotes the length of the decision horizon. The decision horizon is divided into \mathbf{H} time steps ($\Delta\mathbf{t}$). The forecast errors (for the renewable generation and non-controllable loads) are represented through Gaussian probability distribution functions selected according to [222] and [75]. Note that in this paper, we assume that the renewable energy sources of all the MGs are controlled through a maximum power point tracking mechanism, therefore, always generating maximum available power. This implies that the renewable power does not appear as a decision variable in the optimization problem.

Objective Functions and Constraints

Each MG is modeled as a community of cooperative micro-sources with different sets of objective functions and constraints, where each micro-source is controlled by its control agent. Each MG is assumed to be equipped with the following micro-sources (some of which are non-controllable): Photo-Voltaic (PV) power source, thermal Dispatchable Generation (DG) unit, Energy Storage System (ESS), fixed (non-controllable) load, and controllable Demand Response (DR) resources (i.e., curtailable loads). The following objective functions are considered for the dispatchable micro-sources of each MG. The objective functions are denoted as $U_{j,i}^m$, indicating the j^{th}

objective of the i^{th} micro-source of the m^{th} MG.

$$U_{1,1}^m = \sum_{t=1}^H \{-P_G^m(t)\lambda_R(t) - (\mathbf{a}^m \cdot P_{DG}^m(t)^2 + \mathbf{b}^m \cdot P_{DG}^m(t) + \mathbf{c}^m)\} \quad (6.1)$$

$$U_{2,1}^m = \frac{1}{H} \cdot \sum_{t=1}^H \left\{ \frac{k \cdot P_{DG}^m(t)}{\mathbf{a}^m \cdot P_{DG}^m(t)^2 + \mathbf{b}^m \cdot P_{DG}^m(t) + \mathbf{c}^m} \right\} \quad (6.2)$$

$$U_{1,2}^m = \frac{1}{H} \cdot \sum_{t=1}^H \{\lambda_R(t) \cdot P_f^m(t) \cdot (1 - e^{-\omega^m(P_f^m(t) - P_C^m(t))})\} \quad (6.3)$$

$$U_{2,2}^m = \sum_{t=1}^H \{-P_C^m(t)\lambda_R(t)\} \quad (6.4)$$

$$U_{1,3}^m = \sum_{t=1}^H \{-(P_G^m(t))^2\} \quad (6.5)$$

where, $U_{1,1}^m$ and $U_{2,1}^m$ represent the two objectives of the DG agent of the m^{th} MG, denoting profitability of local power generation and average efficiency of operation, respectively. Here, $P_G^m(t)$ is the m^{th} MG's overall exchanged power with the distribution system (under the retail price $\lambda_R(t)$), with $P_G^m \leq \mathbf{0}$ representing power export to the grid and $P_G^m \geq \mathbf{0}$ implying power import from the grid. Also, Coefficients \mathbf{a}^m , \mathbf{b}^m , and \mathbf{c}^m define the quadratic cost function of the DG [167], with $P_{DG}^m(t)$ denoting the output power of the DG unit. Two objective functions, $U_{1,2}^m$ and $U_{2,2}^m$ are also considered for the curtailable DR resources, representing a concave penalty function for load reduction, [60], and cost-savings function, respectively. Hence, deviations from the target (forecasted) fixed load value ($P_f^m(t)$) are penalized through $U_{1,2}^m$, based on the aggregate participation propensity of consumers, defined by ω^m for the m^{th} MG (with $P_C^m(t)$ denoting the aggregate operating power of

the curtailed load). Finally, $U_{1,3}^m$ is the objective function considered for the main MG agent (of the m^{th} MG) to encourage self-sufficiency and avoid over-loading and congestion at the MG's PCC [174]. As shown in equations (6.1)-(6.5), the objective functions are defined as the summation/average over the whole decision window. However, in general only the optimal outcomes for the immediate time step within the decision window are used for power management and the rest are discarded or used for initialization in the future rounds of bargaining as the decision window rolls along time.

Apart from the introduced objective functions, the following constraints are considered for the control agents within each MG:

$$P_{DG}^{min,m} \leq P_{DG}^m(t) \leq P_{DG}^{max,m} \quad (6.6)$$

$$\frac{|P_{DG}^m(t) - P_{DG}^m(t-1)|}{\Delta t} \leq GRC^m \quad (6.7)$$

$$P_{ESS}^{min,m} \leq P_{ESS}^m(t) \leq P_{ESS}^{max,m} \quad (6.8)$$

$$SOC^m(t) = SOC^m(t-1) - \frac{\Delta t}{E_{max,m}} \cdot P_{ESS}^m(t) \quad (6.9)$$

$$SOC^{min,m} \leq SOC^m(t) \leq SOC^{max,m} \quad (6.10)$$

$$P_C^{min,m} \leq P_C^m(t) \leq P_C^{max,m} \quad (6.11)$$

$$P_G^{min,m} \leq P_G^m(t) \leq P_G^{max,m} \quad (6.12)$$

$$P_{DG}^m(t) + P_{PV}^m(t) + P_{ESS}^m(t) + P_G^m(t) + P_C^m(t) = P_f^m(t) \quad (6.13)$$

where, constraints (6.6) and (6.7) define the minimum/maximum generation limits ($P_{DG}^{min,m}$, $P_{DG}^{max,m}$) and the Generation Rate Constraint (GRC) of the DG control agent (for the m^{th} MG), which defines the ramping speed of the units. The ESS is also equipped with a control agent to enforce constraints (6.8), (6.9), and (6.10), which define the minimum/maximum power boundaries ($[P_{ESS}^{min,m}, P_{ESS}^{max,m}]$), and the State Of Charge (SOC) limits ($[SOC^{min,m}, SOC^{max,m}]$). $P_{ESS}^m(t)$ and $E_{max,m}$ denote the power output and the energy capacity of the ESS unit of the m^{th} MG. Constraint (6.11) maintains the curtailed load power between its minimum and maximum limits ($[P_C^{min,m}, P_C^{max,m}]$). Note that curtailable load resources are available only at specific time intervals, not always. The congestion constraint is shown in (5.16) to keep the exchanged power of each MG at the PCC within the permissible boundaries ($[P_G^{min,m}, P_G^{max,m}]$). Finally, the MG-wide power balance constraint is shown in (6.13) for the m^{th} MG. Note that in this equation, $P_{PV}^m(t)$ denotes the power output of the PV resource of the MG at time t (for the m^{th} MG).

While constraints (6.6)-(6.13) are maintained at the lowest level of the bargaining model by the control agents of the micro-sources of each MG, the multi-MG-system-wide power balance constraint, including all the MGs should also be considered in the bargaining process:

$$P_{Ex}^{max} \leq \sum_{m=1}^M P_G^m(t) \leq P_{Im}^{max} \quad (6.14)$$

where, \mathbf{M} denotes the number of MGs. Hence, through (6.14) the total exchanged power of the MGs with the utility company is kept within the maximum export/import limit boundaries ($[\mathbf{P}_{Ex}^{max}, \mathbf{P}_{Im}^{max}]$). In general, the power flow constraints on the distribution network, connecting the MGs, can be introduced in the optimization problem using DC power flow approximation, as described in [21]:

$$\mathbf{P}_l^{min} \leq \{\mathbf{P}_l = \mathbf{H}_N \cdot \mathbf{P}_G\} \leq \mathbf{P}_l^{max} \quad (6.15)$$

where, \mathbf{H}_N represents the matrix of shift factors for the distribution network [21], \mathbf{P}_l denotes the power flow vector of the distribution network, and \mathbf{P}_G is the vector of power export/import of the MGs (i.e., $\mathbf{P}_G = [P_G^1 \dots P_G^M]^T$). \mathbf{P}_l^{min} and \mathbf{P}_l^{max} define the minimum and maximum flow limit vectors on the lines of the network, respectively. Mathematically, the constraint (6.14) itself is a special case of the constraint (6.15).

Note that except for the control agents of MGs at the PCC (which are in charge of maintaining the constraints related to variables $\mathbf{P}_G^m(\mathbf{t})$), the control agents of the micro-sources of MGs are “unaware” of the system-wide power balance and the network power flow constraints ((6.14) and (6.15)). However, these constraints affect the operating point of the micro-sources indirectly. In this way, the bargaining procedure is divided into two levels (which take place simultaneously): at the lower level, a distributed MO optimization problem is solved, through internal bargaining of all micro-source control agents of each MG (with objective functions (6.1)-(6.5), subject to local MG-wide constraints (6.6)-(6.13)). Hence, this layer represents the most local portion of the decision model. At the upper level, the system-wide power balance constraints (6.14) (and (6.15)) are maintained through inter-MG negotiations. This functional separation within the multi-level bargaining structure leads to reduction in communication overheads and a sparse system-wide

communication network, hence increasing the solution speed. Therefore, while at the lower level, the control agents of the micro-sources of each MG can enjoy full connectivity with each other, at the upper level, only the main control agents of the MGs at the PCC need to be connected to each other. Basically, the upper layer shields the lower layer agents from the inter-MG/global communication by eliminating unnecessary interaction links. As will become clear in the next subsection, from the perspective of the computational process (NBS and DSGA), there is no distinction between the lower and upper layers. Both of these layers are part of the same optimization problem (NBS), which is solved using DSGA, through a given communication network.

To summarize, the vectors of objective functions and constraint sets of the control agents within each MG are shown below (in this paper, vector and matrix quantities are shown in bold letters):

1. DG agent: $\mathbf{U}_1^m = [U_{1,1}^m \ U_{2,1}^m]^T$ and $\mathbf{X}_1 = \{(6.6) \cap (6.7) \cap (6.13)\}$.
2. DR agent: $\mathbf{U}_2^m = [U_{1,2}^m \ U_{2,2}^m]^T$ and $\mathbf{X}_2 = \{(6.11) \cap (6.13)\}$.
3. PCC agent: $\mathbf{U}_3^m = [U_{1,3}^m]^T$ and $\mathbf{X}_3 = \{(6.12) \cap (6.13) \cap (6.14)\}$.
4. ESS agent: $\mathbf{U}_4^m = \emptyset$ and $\mathbf{X}_4 = \{(6.8) \cap (6.9) \cap (6.10) \cap (6.13)\}$.

where, \mathbf{X}_i denotes the feasible decision region of the i^{th} agent. Note that each agent has access to a private set of objective functions and a number of constraints, some of which are common among the agents (e.g., MG-wide power balance constraint). In the next subsection, the distributed optimization algorithm is described in details.

Distributed Optimization Algorithm

The concept of NBS [132] is employed to obtain a “fair”, unique, and Pareto-optimal solution to the MO power management problem of the multi-MG system.

Another advantage of NBS is that it can be obtained using a fully distributed computational process, within an agent-based framework. Hence, NBS provides a solution to the bargaining problem of a community of “cooperative” agents (i.e., cooperative MGs). A detailed description of NBS can be found in [132] [45].

The original MO power management problem of the multi-MG system is as follows:

$$\begin{aligned}
& \max_{\mathbf{P}} \{U_{1,1}^1, U_{2,1}^1, U_{1,2}^1, U_{2,2}^1, U_{1,3}^1, \dots, \\
& U_{1,1}^m, U_{2,1}^m, U_{1,2}^m, U_{2,2}^m, U_{1,3}^m\}, \\
& \text{s.t. (6.6) – (6.15), } \forall m
\end{aligned} \tag{6.16}$$

where, \mathbf{P} is the vector of decision variables, consisting of the power of controllable micro-sources of all the MGs (including the exchanged power values with the main grid) for the look-ahead time in which the power management problem is solved. The objective functions in (6.16) are concave and the feasibility region (constraints of (6.16)) is convex [26]. Thus, NBS is well-defined [132], and can be obtained as follows:

$$\begin{aligned}
& \max_{\mathbf{P}} \left\{ \sum_{m=1}^M \sum_{i=1}^{N_m} \log \left(\prod_{j=1}^{O_i^m} (U_{j,i}^m - d_{j,i}^m) \right) \right\}, \\
& \text{s.t. (6.6) – (6.14), } \forall m
\end{aligned} \tag{6.17}$$

where, N_m denotes the number of control agents within the m^{th} MG and O_i^m defines the number of objective functions of the i^{th} control agent in the m^{th} MG. Also, $d_{j,i}^m$'s represent the disagreement points of the bargaining process (i.e., worst case scenarios) [132]. Optimization problem (6.17) has a distributed sum structure, which

can be written as:

$$\begin{aligned} \min_{\mathbf{x}_1, \dots, \mathbf{x}_N} \left\{ \sum_{i=1}^N f_i(\mathbf{x}_i) \right\}, \\ \text{s.t. } \mathbf{x}_i \in X_i \end{aligned} \quad (6.18)$$

where, \mathbf{x}_i denotes the decision vector of the i^{th} agent (with N being the number of agents). The cost function for each agent is represented by $f_i(\mathbf{x}_i)$. For the NBS-based power management problem at hand, the decision vector of each agent is the power vector of the micro-sources in the system (i.e., $\mathbf{x}_i = \mathbf{P}_i$) and the cost function is as follows:

$$f_i(\mathbf{P}_i) = -\log\left(\prod_{j=1}^{O_i^m} (U_{j,i}^m - d_{j,i}^m)\right). \quad (6.19)$$

As shown in [149] and [150], problems of the form (6.18) can be solved using the distributed optimization technique, DSGA. Employing the DSGA and applying it to (6.17), the distributed cooperative bargaining framework for obtaining the NBS is obtained. At each iteration of the algorithm the following steps are performed by each control agent:

- **Step I:** at the k^{th} iteration of the algorithm, each agent receives the estimated solution vectors of its neighboring agents.
- **Step II:** the i^{th} agent performs a weighted averaging operation (with weights a_i^l) over the received signals from its neighboring agents (including its own estimated solution):

$$\boldsymbol{\omega}_i(\mathbf{k}) = \sum_{l=1}^{Ne_i} a_i^l \mathbf{P}_l(\mathbf{k}) \quad (6.20)$$

where, $\mathbf{N}e_i$ denotes the i^{th} agent's number of neighboring agents (including the i^{th} agent).

- **Step III:** at this step, each agent performs a gradient descent operation, as follows:

$$\mathbf{v}_i(\mathbf{k}) = \boldsymbol{\omega}_i(\mathbf{k}) - \alpha_k \cdot \nabla_{\mathbf{P}_i} f_i(\mathbf{P}_i(\mathbf{k})) \quad (6.21)$$

where, α_k is a time-varying weight factor and is selected as $\alpha_k = \frac{\gamma}{k+1}$, with γ acting as a tunnable parameter of the model. The gradient of the cost function for the NBS formulation (6.17) is obtained as follows:

$$\nabla_{\mathbf{P}} f_i(\mathbf{P}) = - \begin{bmatrix} \frac{\partial U_{1,i}^m}{\partial P_1} & \cdots & \frac{\partial U_{O_i^m,i}^m}{\partial P_1} \\ \vdots & \ddots & \vdots \\ \frac{\partial U_{1,i}^m}{\partial P_L} & \cdots & \frac{\partial U_{O_i^m,i}^m}{\partial P_L} \end{bmatrix} \begin{bmatrix} \frac{1}{U_{1,i}^m - d_{1,i}^m} \\ \vdots \\ \frac{1}{U_{O_i^m,i}^m - d_{O_i^m,i}^m} \end{bmatrix} \quad (6.22)$$

- **Step IV:** each agent projects the outcome of Step II into its private feasible region (given in Section II) to update its estimated solution for the next iteration:

$$\mathbf{P}_i(\mathbf{k} + 1) = \Pi_{X_i} \{ \mathbf{v}_i(\mathbf{k}) \} \quad (6.23)$$

where, Π_{X_i} defines the projection operation into the set X_i . Note that the projection operation is a convex quadratic programming problem [26], which is formulated as follows:

$$\begin{aligned} \Pi_{X_i} \{ \mathbf{v}_i(\mathbf{k}) \} &= \arg \min_{\mathbf{y}} \|\mathbf{y} - \mathbf{v}_i(\mathbf{k})\| \\ &s.t. \mathbf{y} \in X_i \end{aligned} \quad (6.24)$$

where, $\|\cdot\|$ is the Euclidean norm.

- **Step V:** The agents send their updated estimated solutions (i.e., $\mathbf{x}_i(\mathbf{k} + 1)$)

to their neighbors.

Utility Company's Decision Model

At the highest level of the decision model, the utility company which acts as a mediator agent between the wholesale market and the cluster of cooperative MGs performs the two following steps:

- **Model Development:** The utility company develops a model to assess the aggregate price-sensitivity of the MGs (i.e., system identification). Note that the utility company does not have direct access to the decision problem of the MG agents. Price signals ($\boldsymbol{\lambda}_R$) are sent to the main MG agents and the estimated power export/import signals are received back from the MGs (as feedback signals). Based on these interactions a “learning” procedure is executed in which a price-sensitivity model (denoted as Γ) is fit to the response of the MGs (i.e., $\mathbf{P} = \Gamma(\boldsymbol{\lambda})$). In this paper, we have employed a multiple linear regression strategy for model development [48]:

$$\mathbf{P}_a = \mathbf{A}\boldsymbol{\lambda}_R + \mathbf{P}_0 \quad (6.25)$$

where, $\boldsymbol{\lambda}_R$ is the retail price vector, matrix \mathbf{A} and vector \mathbf{P}_0 are the time-varying parameters of the model that are learned through QR-decomposition [109]. \mathbf{P}_a represents the aggregate sold/bought power from the cluster of MGs. Hence, at each iteration of the learning process the utility company “excites” the MGs with a price signal, which serves as an input data sample in the model. The aggregate feedback power signal (the aggregate of signals received from the main MG agents) acts as an output data sample in the learning process. After enough data samples are collected to ensure that the problem of model over-fitting is

avoided, the learned model is used by the utility company for future use. A detailed formulation of (6.25) is given below:

$$\begin{bmatrix} \sum_{m=1}^M P_G^m(\mathbf{1}) \\ \vdots \\ \sum_{m=1}^M P_G^m(\mathbf{H}) \end{bmatrix} = \begin{bmatrix} \mathbf{a}_{11} & \dots & \mathbf{a}_{1H} \\ \vdots & \ddots & \vdots \\ \mathbf{a}_{H1} & \dots & \mathbf{a}_{HH} \end{bmatrix} \begin{bmatrix} \lambda_R^1 \\ \vdots \\ \lambda_R^H \end{bmatrix} + \begin{bmatrix} P_0^1 \\ \vdots \\ P_0^H \end{bmatrix} \quad (6.26)$$

- Retail Price Generation:** Based on the learned model, the utility company calculates the optimal retail price to achieve its own objectives. Two objective functions are considered in this paper, corresponding to the two stages of the market: at the DA stage the objective of the utility company is to maximize its profit through sale/purchase of power to/from the MGs, using the forecasted values for different variables in the system. Hence, a DA aggregate power profile is obtained from the MGs, based on the optimal DA retail prices, which is then submitted to the wholesale market. However, in RT due to the changes in the system variables and structure (e.g., prediction error, MG islanding, etc.) deviations from the DA schedule could occur. At the RT stage, the goal of the utility company is to fulfill the submitted DA power profile, using RT retail pricing (computed by the utility company) in order to minimize this deviation. Hence, we assume that the priority of the utility company is to compensate the deviations between the total DA and RT aggregate power of the MGs (any deviation is penalized in the RT wholesale regulation market.)

The Optimization problems corresponding to utility company's decision model at the DA and RT stages are as follows:

DA Retail Pricing: The objective function of the utility at this stage is to

maximize the DA profit level from power exchange.

$$\begin{aligned}
& \min_{\lambda_{R,DA}} \{ -\lambda_{R,DA}^T \cdot A \cdot \lambda_{R,DA} + (\lambda_{W,DA}^T \cdot A - P_0^T) \lambda_{R,DA} \\
& \quad + (\lambda_{W,DA}^T \cdot P_0) \}, \\
& \quad s.t. \begin{cases} \lambda_{R,DA}^{min} \preceq \lambda_{R,DA} \preceq \lambda_{R,DA}^{max} \\ (\lambda_{R,DA} - \lambda_{W,DA})^T \cdot \Gamma(\lambda_{R,DA}) \leq \pi^{max}, \end{cases}
\end{aligned} \tag{6.27}$$

where, $\lambda_{R,DA}$ and $\lambda_{W,DA}$ denote the DA retail and wholesale price vectors, respectively. Also, “ \preceq ” denotes the vector form of operator “ \leq ”. The constraints of the optimization problem define the minimum/maximum boundaries on the price vector ($[\lambda_{R,DA}^{min}, \lambda_{R,DA}^{max}]$), and a maximum DA profit level for the retailer (i.e., π^{max}). Optimization problem (6.27) is a case of Quadratically Constrained Quadratic Programming (QCQP) [26].

RT Retail Pricing: At this stage, the objective function of the utility is to minimize the deviation between the aggregate RT power profile of the MGs and the scheduled DA plan (P_{DA} , obtained from the DA stage) by obtaining optimal retail prices:

$$\begin{aligned}
& \min_{\lambda_{R,RT}} \{ \lambda_{W,RT} \cdot \|\Gamma(\lambda_{R,RT}) - P_{DA}\| \}, \\
& \quad s.t. \lambda_{R,RT}^{min} \preceq \lambda_{R,RT} \preceq \lambda_{R,RT}^{max}
\end{aligned} \tag{6.28}$$

where, $\lambda_{R,RT}$ and $\lambda_{W,RT}$ are the RT retail and wholesale price vectors, respectively. The only constraint considered at this stage is to keep the price within its minimum/maximum boundaries ($[\lambda_{R,RT}^{min}, \lambda_{R,RT}^{max}]$). Fig. 6.1 shows the interaction structure of the retail market agent (utility company) with the wholesale market and

the MG-based energy network.

Simulation Results and Discussion

The proposed decision framework is tested in a power system with three MGs. Each MG is based on modified versions and variations of the IEEE 13-bus standard distribution network used in our earlier work [45]. The PV power profiles of different MGs are adopted from [59] and shown in Fig. 6.2. The fixed load data for the three MGs, shown in Fig. 6.3, are obtained from [152] and [83], and the wholesale DA and RT market prices are adopted from [28].

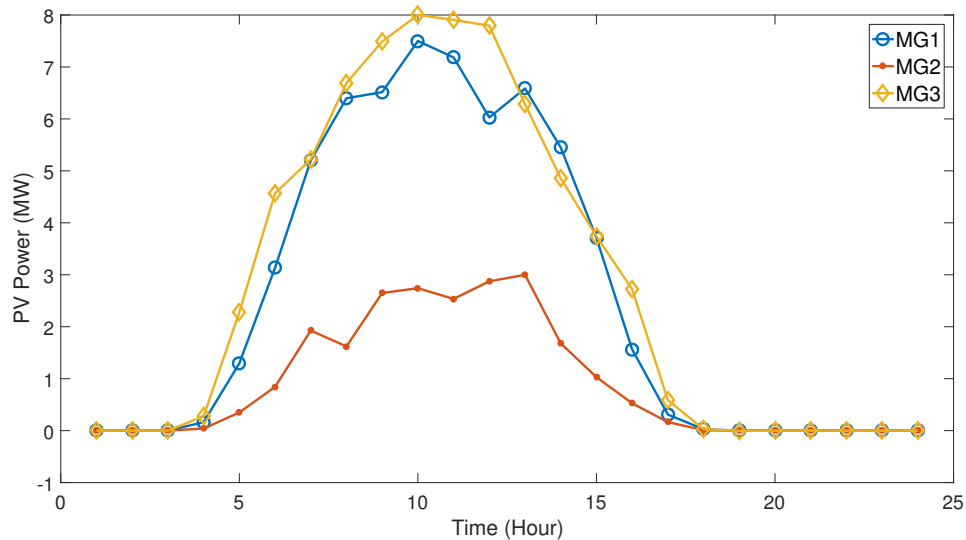


Figure 6.2: PV power data for the different MGs

In the simulation experiment scenario we assume that all the three MGs participate in the DA retail market. However, in the RT stage, we assume a disturbance (one of the MGs is islanded from the distribution system for the whole day, performing internal single-MG bargaining as described in [45].) Based on this scenario, the numerical results are discussed in the rest of this section.

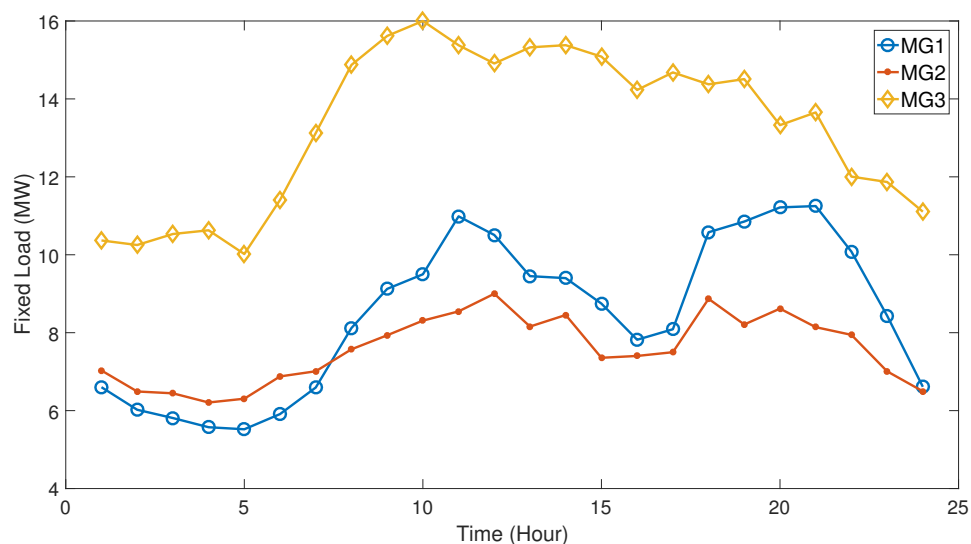


Figure 6.3: Fixed load profiles of the different MGs

A. DA Stage: On the utility company’s side, the learning process performed by the utility leads to low prediction errors, as can be seen in Fig. 6.4 (i.e., after a transient stage the utility company is able to predict the aggregate response of the MGs to the price signal with high accuracy using the developed model). The Mean Absolute Error (MAE) of power prediction reaches a value of 2% through the iterations. As the model development step is completed, the result of optimal pricing for the DA retail market is shown in Fig. 6.5. Also, the individual and aggregate exported power of the three MGs under the optimal DA retail prices are shown in Fig. 6.6. As is observed in these figures, the utility company “buys” power from the MGs at the optimal retail price and sells it on the DA wholesale market at a higher wholesale price (Fig. 6.5). Hence, the price-sensitivity of the distribution system leads to lower energy prices at the retail level compared to the wholesale level. Also, it can be seen that as the value of the retail price signal increases, the power export levels of the MGs increase as well (i.e., MGs “sell” more power to the utility company

at higher retail prices).

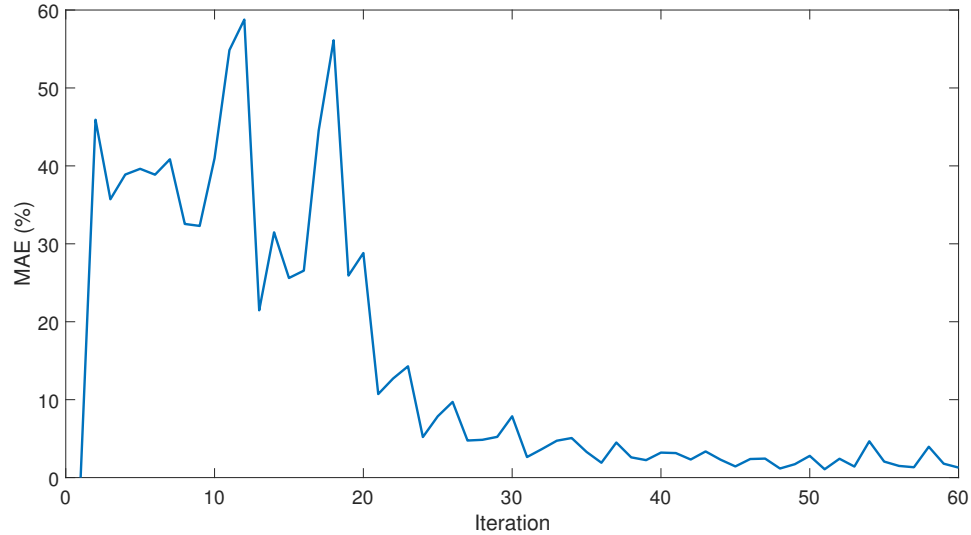


Figure 6.4: Utility company's power prediction error

The DA profit profile of the utility company is shown in Fig. 6.7. As can be seen in this figure, higher power exports to the wholesale market results in intervals of higher profit for the utility company. Also, the total profit level of the utility company for the whole day throughout the learning process (i.e., model development iterations) is demonstrated in Fig. 6.8. As is shown in this figure, the profit level of the utility company improves and reaches its maximum level, as the learning process produces a reliable model of the price-sensitivity of the MGs for the utility company.

The DA power profiles of the DG units of the MGs is shown in Fig. 6.9. As can be seen in this figure, the three DG units of the MGs provide a base load at the earlier hours of the day. But, at later hours, the DG units increase their power output due to higher retail price levels, which makes power generation more profitable. The same principle applies to the ESS units. As shown in Fig. 6.10, the ESS units

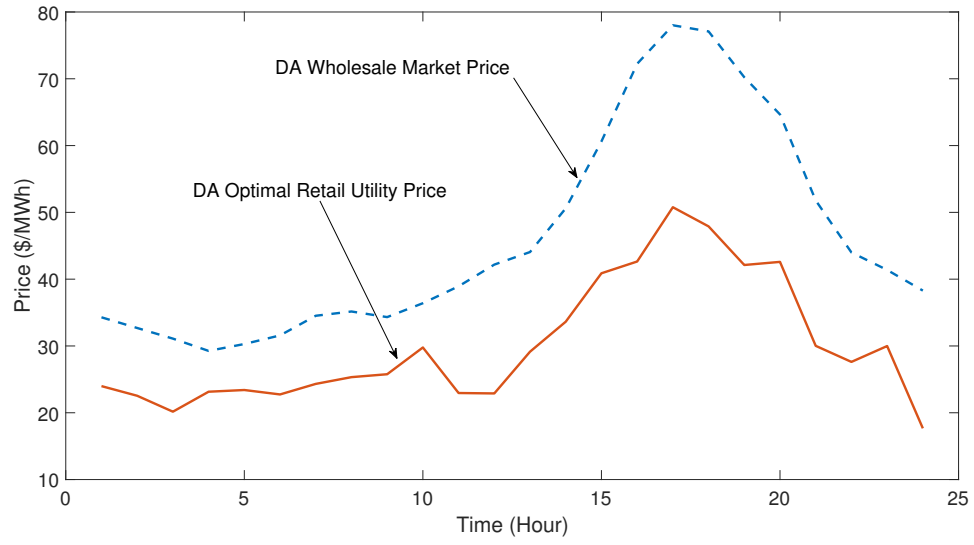


Figure 6.5: DA wholesale/retail prices

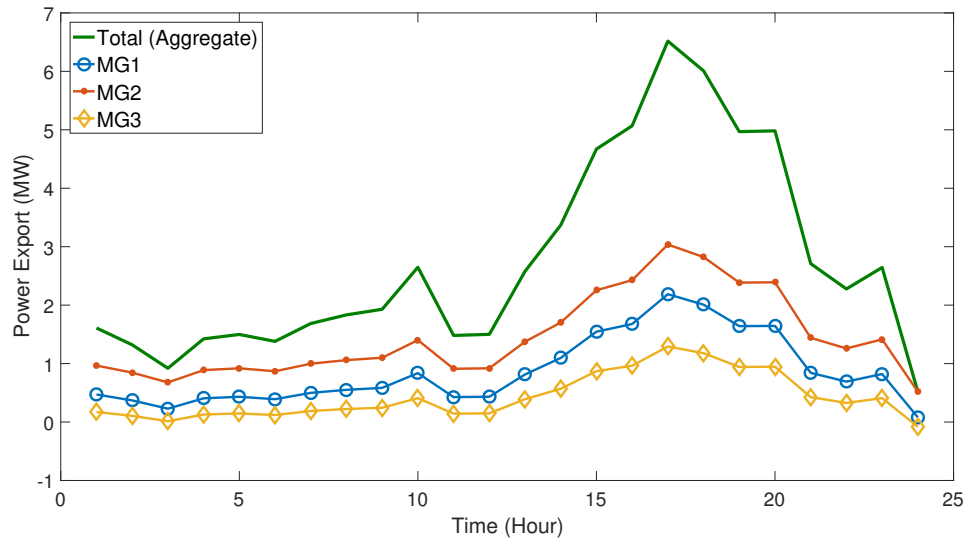


Figure 6.6: MGs' power exchange with the utility company

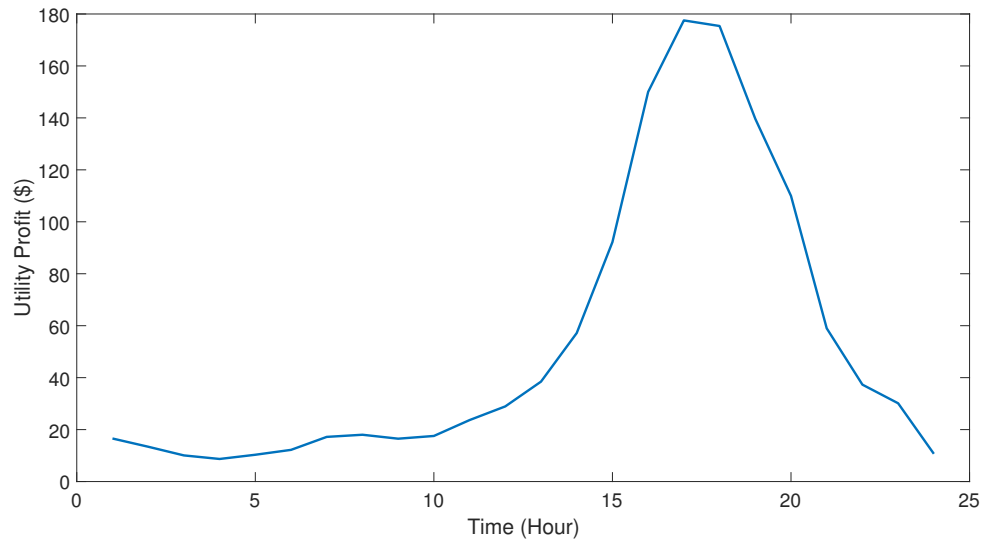


Figure 6.7: Utility company's hourly profit profile

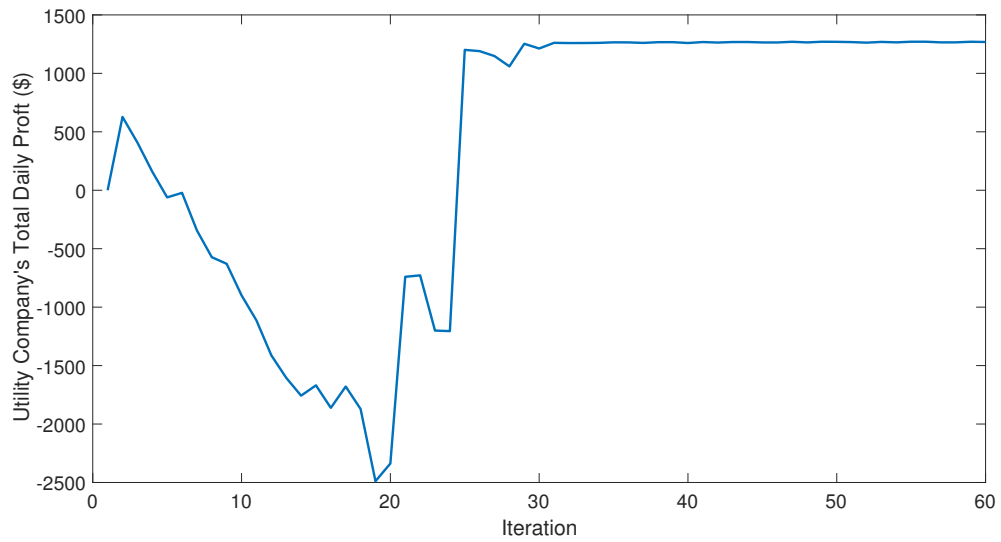


Figure 6.8: Utility company's daily total profit profile throughout the learning process

are in charging state at earlier hours of the day with lower retail prices (negative power implies charging), and discharging state at the later hours during the high price interval. The stored energy profile (DA SOC) of the ESS units are shown in Fig. 6.11, along with the minimum/maximum allowable energy (SOC) limits ($[E^{min,m}, E^{max,m}]$). It can be observed that the bargaining process has maintained the stored energy levels of the ESS units within the acceptable ranges at all times. The total maximum available and the realized curtailable demand resources (for all MGs) are depicted in Fig. 6.12. While up to a maximum of 20% of the total fixed load is available for curtailment (at hours 19:00 and 20:00), the realized curtailment demand value reaches 11% of the total fixed load (at hours 19:00 and 20:00). This is well below the maximum available level (i.e., only about half of the available DR resources are employed at the peak demand hours.) All the MGs respond to the increase in the price signal, as shown in Fig. 6.6. However, since the MGs are not identical, the increase in the export levels are not equal, and depend on many factors, such as the local demand level of each MG (Fig. 6.3), generator ramping constraints, available PV power (Fig. 6.2), ESS capacity and storage level, etc. For instance, the DG unit of MG1 shows a considerable power output increase in the time span 15:00 20:00. While this increase is partly due to higher retail price (which makes local generation more profitable), it is also caused by higher load levels in MG1 during this time. On the other hand, the discharge rate of the ESS units in all the MGs increase considerably during the peak price time interval (Fig. 6.10), with MG3 showing the maximum increase in discharge power. In addition, the rate and duration of discharge partly depends on the available stored energy level and SOC constraints in the decision model (shown in Fig. 6.11).

B. RT Stage: As discussed previously, we assume that in RT, one of the MGs is islanded during the whole day. This scenario demonstrates the effectiveness

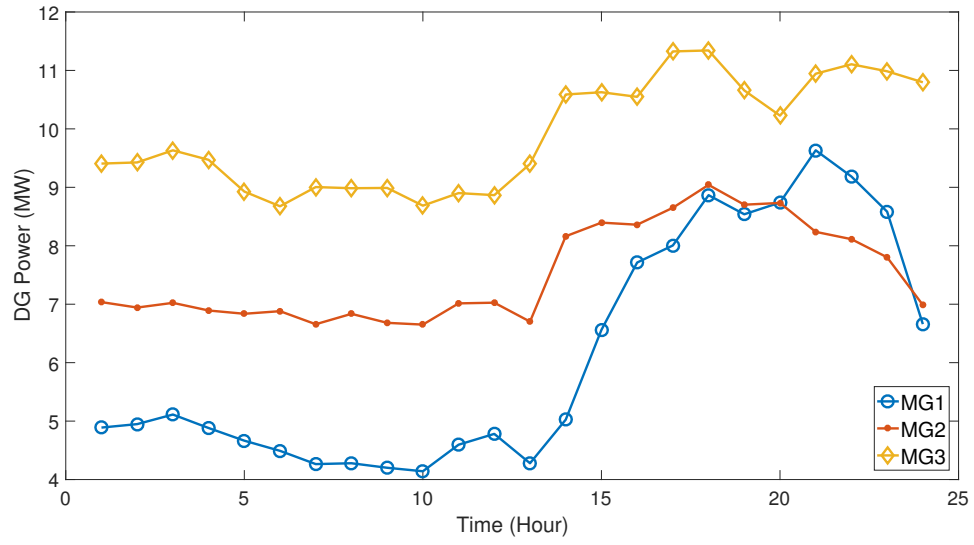


Figure 6.9: DA DG power profile of the MGs

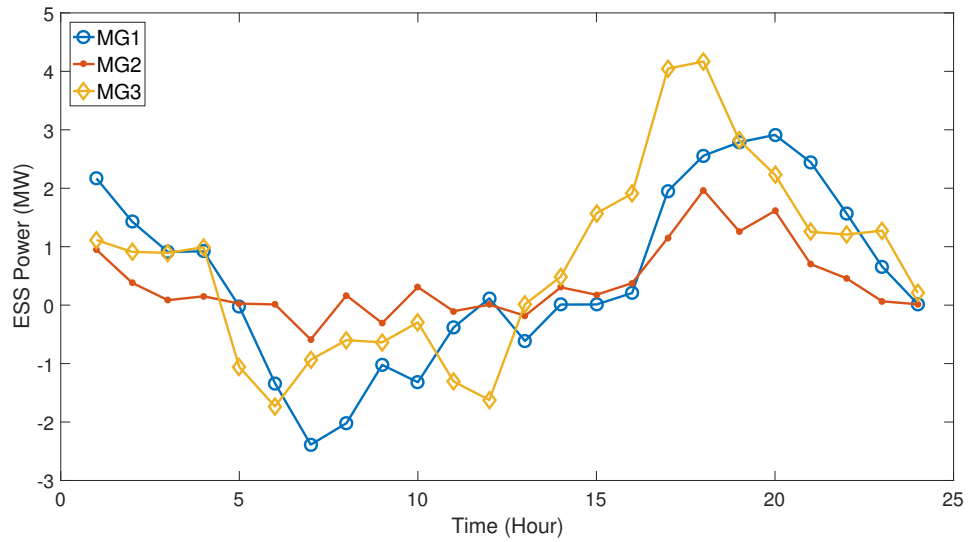


Figure 6.10: DA ESS power profile of the MGs

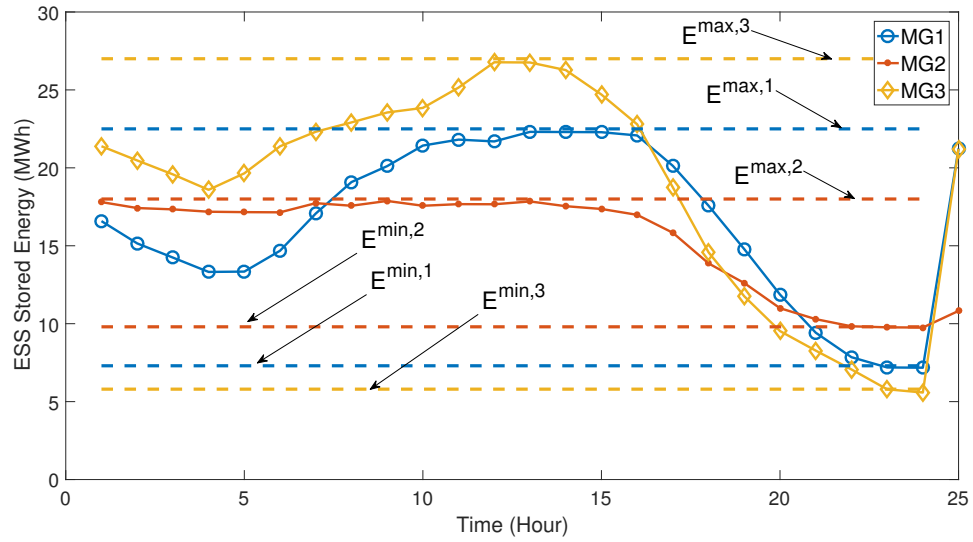


Figure 6.11: DA ESS SOC profile of the MGs

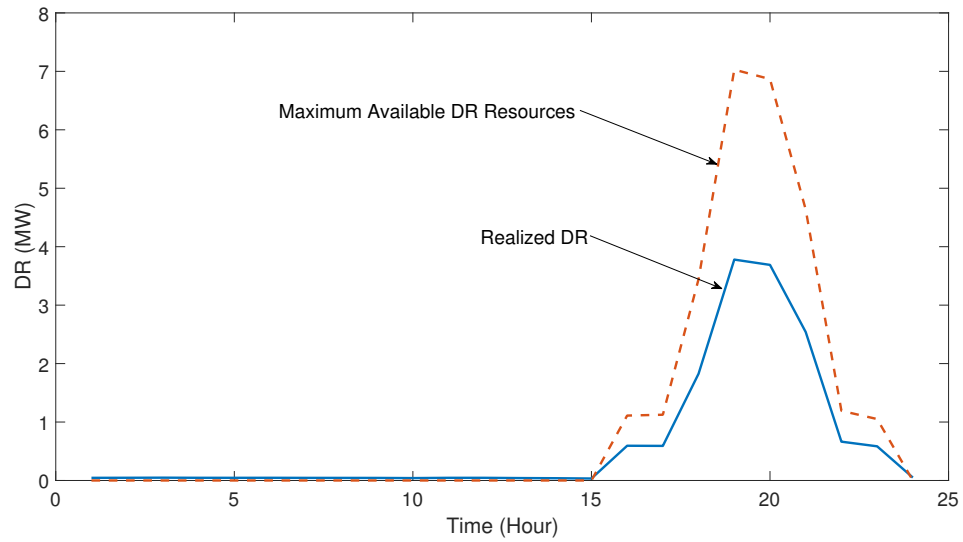


Figure 6.12: DA curtailed aggregate load of the MGs

of the proposed decision scheme in RT, under significant structural changes in the system. The aggregate power export level of the MGs to the wholesale market is shown in Fig. 6.13. As can be seen in this figure, if no corrective action is undertaken by the utility company a large power deficit will occur in RT, due to the islanding of an MG, which results in power generation deficit. However, by solving (6.28) and modifying (increasing) the RT retail prices, the utility company undertakes corrective action to minimize the power deficit by using other available resources in the grid-connected MGs. As is observed in Fig. 6.13, the corrected aggregate power profile of the remaining two MGs under the new RT price is nearly identical to the scheduled DA power profile, even though one of the MGs was islanded. Hence, using corrective action the power mismatch level drops from an overall value of 52.7% to 6% (Fig. 6.13). The optimal RT retail price that achieves this low level of power mismatch is shown in Fig. 6.14. As demonstrated in this figure, a considerable increase in the utility retail price is observed. In other words, the utility company increases the RT retail prices in order to incentivize the non-islanded MGs to produce more power to compensate for the power deficit caused by the islanded MG, and minimize the power mismatch between the RT aggregate profile and the DA power schedule. Hence, the utility is able to find the “correct” RT retail price signal to achieve its objective by indirectly controlling the behavior of the MGs. The changes in power exports of MG2 and MG3 (that are grid-connected) to the utility compared with their DA schedule are shown in Fig. 6.15. As can be seen here, both MGs increase their net output power in response to the new price signal to compensate for the lost power export of the islanded MG, which implies a more flexible and active distribution system with higher levels of controllability.

The penalty levels for the power mismatch values in the RT wholesale market, are shown in Fig. 6.16 for two cases: 1) no corrective action is undertaken in RT

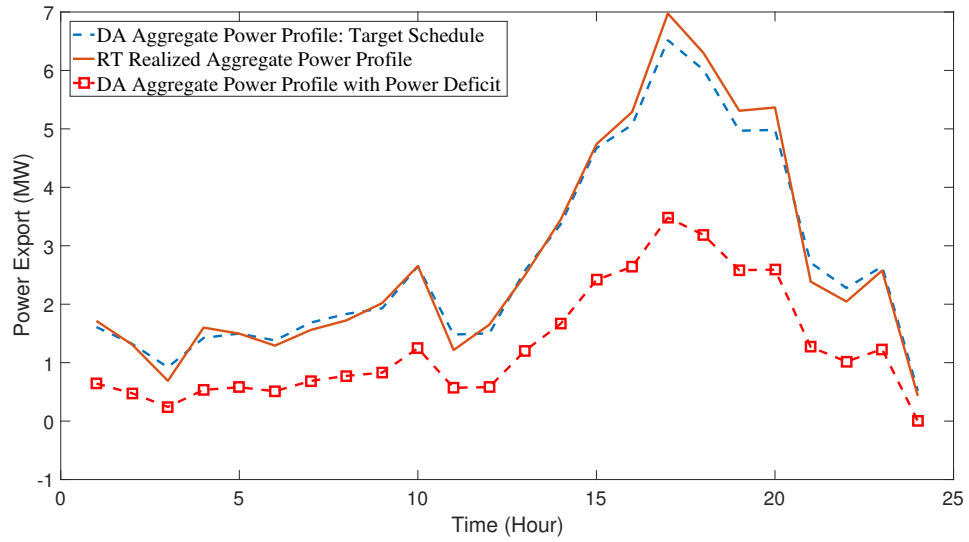


Figure 6.13: Aggregate power profile of the system in RT

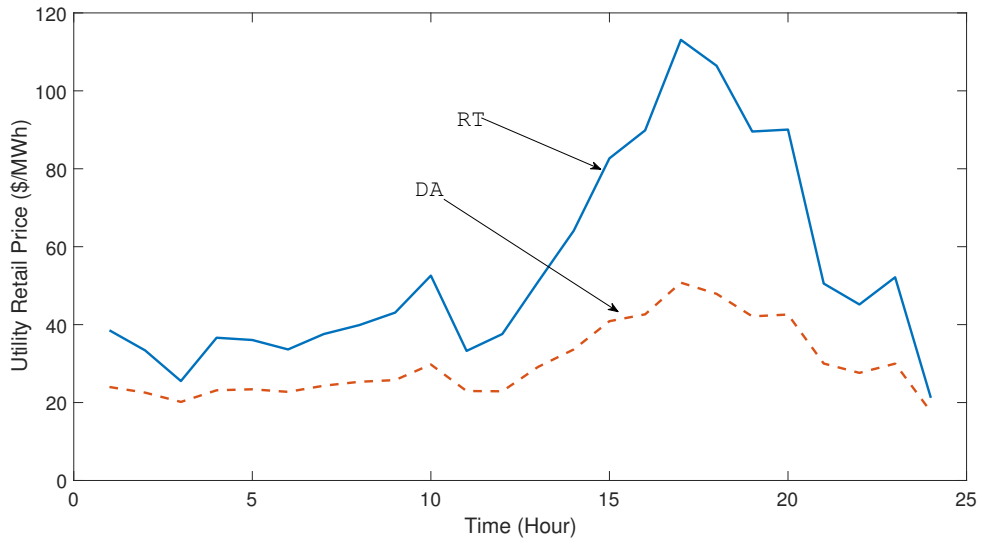


Figure 6.14: Optimal RT retail prices

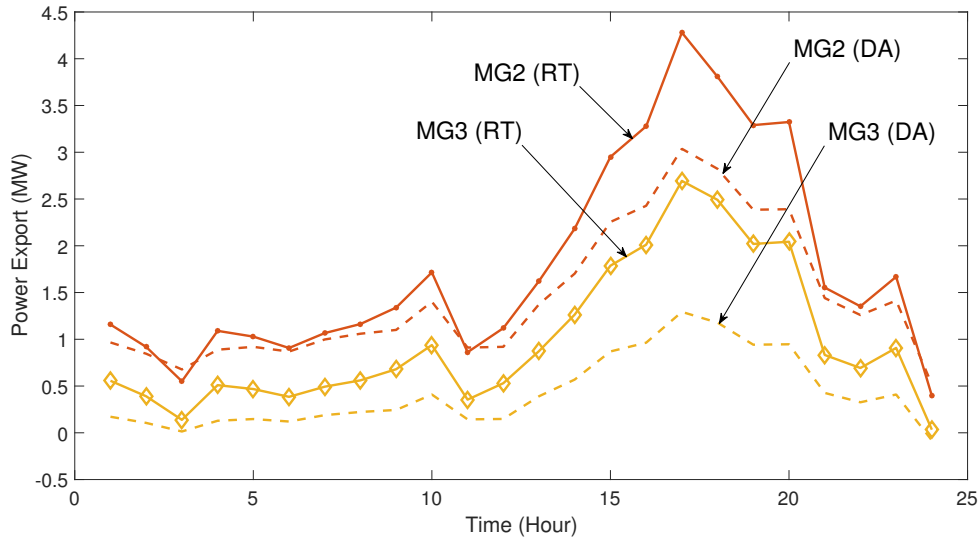


Figure 6.15: Grid-connected MGs' DA and RT power export profiles

by the utility company (i.e., maximum penalty), and 2) corrective RT retail pricing is performed to minimize the power mismatch. Note that the penalty levels define the monetary values paid by the utility company to the wholesale regulation market to compensate for the deviations from the DA power schedule. Here, a drop in the penalty level is also observed through optimal RT pricing. The penalty level drops from a total value of \$1841.6 for the day under case 1 (which is above the utility company's total DA profit of \$1307.2) to \$214.8 for case 2, which implies an 88% improvement. Hence, the RT retail pricing scenario demonstrates the effectiveness of the proposed decision model in providing a safe and economically viable operation margin for different parties in the multi-MG system (including the utility company).

C. Discussion: In order to investigate the suitability of our proposed distributed optimization methodology for RT power management applications, we compared it with a conventional central optimization method available in MATLAB's

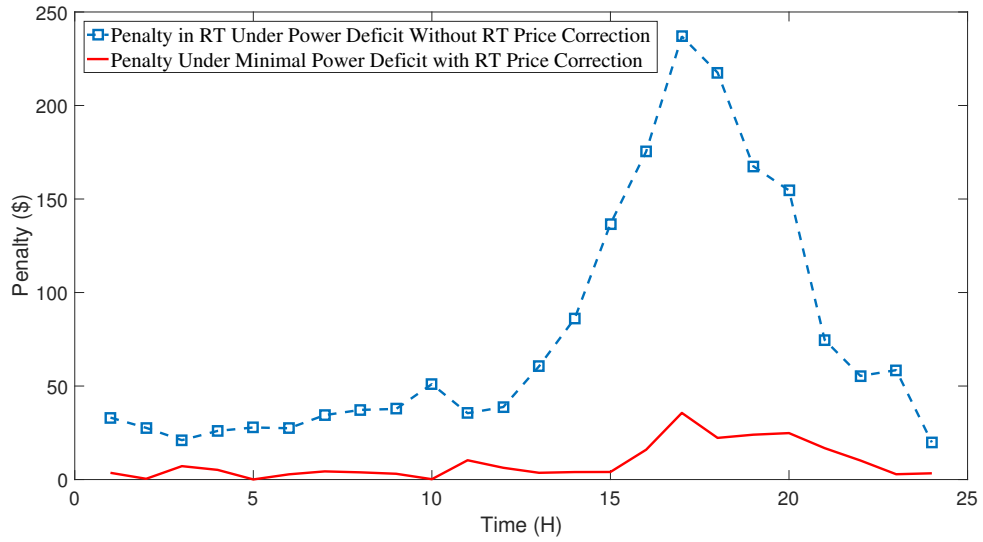


Figure 6.16: Utility company's penalty level in the wholesale market

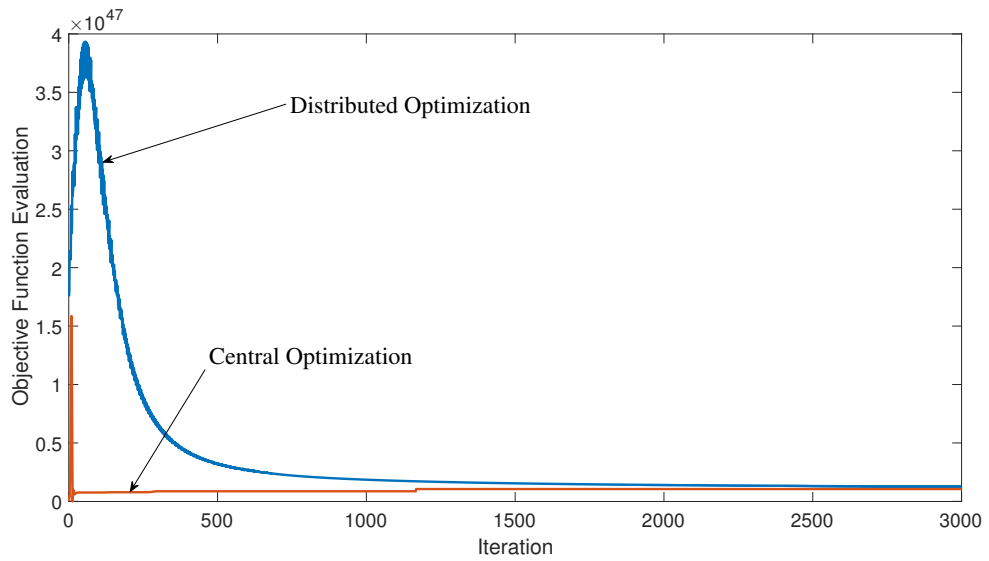


Figure 6.17: Optimization convergence demonstration

optimization toolbox. Due to the convexity of the decision model, both the central and the proposed distributed optimization methods yield the exact same results. Fig. 6.17 shows the convergence of the two optimization methods for one round of bargaining, where, the global objective function of the optimization problem (6.17) is evaluated at different iterations of the optimization solvers. As shown in the figure, the two methods converge to the same value in each round of bargaining. Although, the distributed optimization method has a longer transient period, its convergence time is much shorter. While our proposed distributed bargaining technique converged in around 15 minutes per round, the convergence of the central optimization took about one hour. This indicates that the conventional central optimization method has a much higher computational load per iteration, compared to our proposed distributed optimization technique. We used one computer to perform the agent-based distributed MO optimization, whereas in practice different computers and computational resources are used for each agent to perform their tasks. This leads to even less computational delays compared to the case where all agents are implemented on the same machine. Also, note that by reducing the look-ahead time horizon of the algorithm (i.e., \mathbf{T}) this computational time can be further improved. Hence, we believe that the proposed distributed bargaining technique is suitable for real-time applications in power systems.

Conclusion

In this paper, an agent-based hierarchical MO decision model is proposed to handle the power management problem of an energy network with multiple MGs. At the lower and upper levels of the model the cooperative cluster of MGs bargain with each other to reach a fair and Pareto-optimal solution, employing the concept of NBS within a distributed optimization framework. At the highest level, a utility

company sets the retail prices for the MGs to achieve its own objective through power exchange with the MGs at the DA and RT market stages. The utility company is able to pursue its goals solely based on optimal energy pricing (through a machine learning technique) and without direct access to the internal control process of the MGs. The distributed and agent-based nature of the model eliminates the need for a central control, which leads to an automation system without a single point of failure. This also reduces the computational load of each control agent in the system, which makes the proposed decision model a suitable choice for wide-scale implementation in real-time.

A MARKET-BASED RESILIENT POWER MANAGEMENT TECHNIQUE FOR
DISTRIBUTION SYSTEMS WITH MULTIPLE MICROGRIDS USING A
MULTI-AGENT SYSTEM APPROACH

Contribution of Authors and Co-Authors

Manuscript in Chapter 7

Author: Kaveh Dehghanpour

Contributions: Developed and tested the agent-based probabilistic decision model for improving system resiliency through microgrid power management, and prepared the manuscript.

Co-Author: Hashem Nehrir

Contributions: Supervised the overall flow of the project, and provided important insight on numerical studies and interpretation of the results. Aided in the preparation of the manuscript.

Manuscript Information Page

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Abstract

In this paper, we present a resilient and extreme-event-aware power management procedure for electrical distribution systems consisting of multiple cooperative MicroGrids (MGs). Distributed optimization is used to find the optimal resource allocation for the multiple MG system, while maintaining the local and global constraints, including keeping the voltage levels of the micro-sources within bounds. The proposed method is based on probabilistic reasoning in order to consider the uncertainty of the decision model in preparation for expected extreme events and in case of unit failure, to improve the resiliency of the system. Basically, the power management problem formulation is a multi-objective optimization problem, which is solved using the concept of Nash Bargaining Solution (NBS). The simulation results show that the proposed method is able to improve the resiliency of the system and prepare it for extreme events and unit failure, by increasing power reserve and modifying the operating point of the system to maintain voltage and power constraints across the MGs.

Introduction

Power system resiliency is defined as the grid's ability to withstand high impact disruptive events (e.g., storms, hurricanes, etc.), while continuing to provide energy to critical loads, and restoring services to all consumers after the events, as fast as possible [30]. Hence, as discussed in [7], a crucial aspect of resilient power systems depends on how the designed control and power management systems within the grid respond to these extreme events. Also, as shown in [196], a systemic long-term approach, spanning various agencies and departments, is required to ensure the resiliency of a complex and critical infrastructure, such as the US national grid.

In order to be able to improve the resiliency of the power systems some levels of micro-generation and distributed/local decision making capabilities should be integrated into power systems. In this respect, the concept of self-sufficient MicroGrids (MGs) becomes highly relevant, given the ability of MGs to continue providing service to the consumers in islanded mode. Also, MGs provide an efficient framework for introducing distributed and local control and power management capabilities in distribution systems, which can be exploited to decentralize the decision making procedures in power systems and avoid single-point-of-failure.

The connection between MG operation and resiliency enhancement has been studied in several papers. A non-cooperative game theoretic model is proposed in [37] to address the strategic behavior of MGs, using the concept of Nash equilibrium. Different failure modes are considered in the paper to improve the resiliency of the system. A two-stage resiliency-oriented decision model is presented in [70] for a single MG to mitigate the effect of service interruption, using a stochastic programming technique. Also, in [119] different indexes are introduced to assess the resiliency of power systems consisting of MGs, employing Markov model and Monte Carlo simulation. In [181], MGs are used as resiliency resource (both at local and community levels). A self-healing strategy is proposed in [161] for two neighboring MGs to support each other in times of load deficiency. A self-healing agent is considered that is able to operate in both centralized and decentralized modes. A centralized resiliency-oriented MG scheduling is proposed in [100] for a single MG, which enables it to operate in grid-connected and islanded modes. Another resiliency-based power control scheme for multi-MG systems is proposed in [203], where at the global level a distributed resource allocation problem is solved, whereas at local levels, the scheduling problems are solved centrally within each MG.

This paper is a continuation of our previous works [45] and [46]. In [45], we

employed the concept of Nash Bargaining Solution (NBS) to develop a distributed agent-based Multi-Objective (MO) power management framework for a single MG. Within this framework, the control agents of the different micro-sources of the MG interact with each other to solve a resource allocation problem and reach a unique, Pareto-optimal, and fair solution, employing the Distributed Sub-Gradient Algorithm (DSGA) [149] [150]. The DSGA is a distributed optimization technique, through which a number of agents are able to collectively solve a global optimization problem, only with access to local and private data, through a communication network. In [46], we extended this decision model to multi-MG power distribution systems, by introducing additional layers to the bargaining hierarchy. Also, the impact of interaction of the multi-MG network with a retail market agent on system operation and energy pricing were studied.

In this paper, we further extend our previously proposed cooperative multi-MG power management method to evaluate the resiliency of the system by “preparing” it for extreme events and unit failure, well ahead of time, for look-ahead decision horizons, based on forecasted probability of event occurrence. Note that the post-event real-time operation of the system within a market-based framework is discussed in [46]. To obtain a pre-event preparedness, a new objective function is introduced to the decision problem of each MG. The purpose of this objective function is to minimize the expected loss of load for certain look-ahead times during system operation, based on the predicted chances of unit failure and blackout in the main grid. Thus, we assume that each MG has access to a probabilistic overview of the structure of the system and the environmental conditions around the location of the MG for different look-ahead times (e.g., probability of islanding and unit failure due to extreme events), which gets updated as the decision window rolls along time. This probabilistic overview basically represents the agents’ “belief” on the future state of the system.

Employing this probabilistic model, the agents perform reserve allocation to minimize the chance of service disruption to consumers. This probabilistic objective function is integrated within the distributed decision model. Simulations have been performed with and without the proposed objective function to compare the outcomes of our proposed resiliency-aware power management with the original power management scheme. Also, the model is extended to include the constraints on the voltage magnitude of each micro-source, including the controllable load bus, to maintain them within permissible bounds. Voltage constraints and reactive power allocation are considered in the distributed optimization model, using a convex relaxation of AC power flow [77]. This is achieved by adding reactive power to the decision vector of the micro-sources of the MGs. Different components of the system can be affected during an extreme event (e.g., cables, conductor lines, micro-sources, control system, and communication links). However, the focus of this paper is to evaluate the behavior of the system under islanding and micro-source failure scenarios. An advantage of using the DSGA is that the algorithm is able to converge even for time-varying interaction networks. Hence, even if certain controllers or communication links fail after an event, the rest of the agents that are connected to each other can still find a near-optimal point of operation for their respective micro-sources.

The rest of the paper is constructed as follows: in Section II a summary of the distributed decision model is given. The proposed modifications in the decision model to turn it into a resiliency-aware power management scheme are presented in Section III. The results of the numerical experiments are given and discussed in Section IV. The conclusions of the paper are presented in Section V.

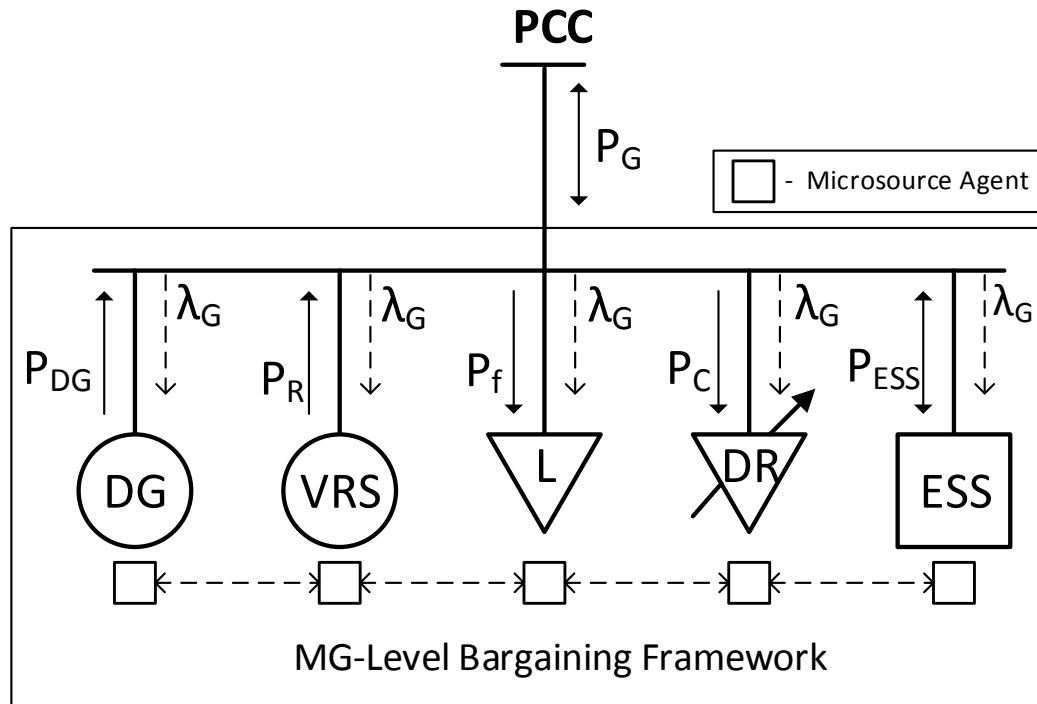


Figure 7.1: Structure of an MG used in the paper [45]

Distributed Bargaining Framework for Multiple MGs

In this section, we give a brief review of the distributed bargaining procedure, which takes advantage of the concept of NBS. The basic idea of this method is that a community of cooperative agents within multiple MGs, with different sets of objective functions and constraints, negotiate with each other to reach a unique, fair, and Pareto-optimal solution. As shown in [132], NBS satisfies these desirable properties. Moreover, NBS can be found through a distributed optimization mechanism, due to its distributed-sum structure [149] [45]. In this paper, we assign a Photo-Voltaic (PV) unit, a Dispatchable Generator (DG) unit, an Energy Storage System (ESS), uncontrollable and curtailable Demand Response (DR) resources to each MG, as shown in Fig. 7.1 [45]. A separate control agent is considered for each micro-source (i.e., the DG, ESS, and DR resources of each MG). Also, a main control agent is in charge of controlling each MG's net power exchange with the main grid, at the Point of Common Coupling (PCC). The PV unit is operated based on the concept of maximum power point tracking; the unit's output power is simply predicted and used as input to the decision problem, based on calculated prediction error distribution discussed in [222]. However, we assume that the PV systems have limited amount of controllable reactive power (due to storage elements at their DC buses), which is controlled by a local agent for voltage regulation at the PV buses. The following objective functions and constraints are considered for the control agents of the micro-sources and main control agent (at the PCC) of each MG, where, $U_{j,i}^m$ indicates the j^{th} objective function of the i^{th} micro-source of the m^{th} MG:

- **DG control agent:**

$$U_{1,1}^m = \sum_{t=1}^H \{-P_G^m(t)\lambda_R(t) - (a^m \cdot P_{DG}^m(t))^2 + b^m \cdot P_{DG}^m(t) + c^m\} \quad (7.1)$$

$$U_{2,1}^m = \frac{1}{H} \cdot \sum_{t=1}^H \left\{ \frac{k \cdot P_{DG}^m(t)}{a^m \cdot P_{DG}^m(t)^2 + b^m \cdot P_{DG}^m(t) + c^m} \right\} \quad (7.2)$$

$$P_{DG}^{min,m} \leq P_{DG}^m(t) \leq P_{DG}^{max,m} \quad (7.3)$$

$$\frac{|P_{DG}^m(t) - P_{DG}^m(t-1)|}{\Delta t} \leq GRC^m \quad (7.4)$$

$$S_{DG}^m(t) = \sqrt{(P_{DG}^m(t))^2 + (Q_{DG}^m(t))^2} \quad (7.5)$$

$$0 \leq S_{DG}^m(t) \leq S_{DG}^{max,m} \quad (7.6)$$

$$V_{DG}^{min,m} \leq |V_{DG}^m(t)| \leq V_{DG}^{max,m} \quad (7.7)$$

$$|V_{DG}^m(t)| \approx 1 + \sum_{j \in \mathcal{N}_{DG}} \{R_{DG,j} P_{DG,j} + X_{DG,j} Q_{DG,j}\} \quad (7.8)$$

where, $U_{1,1}^m$ and $U_{2,1}^m$ represent the profitability of local power generation and average efficiency of operation, respectively. Also, $P_G^m(t)$ denotes the m^{th} MG's power import from the grid (at the retail price $\lambda_R(t)$). Note that $P_G^m \leq 0$ represents power export to the grid. Coefficients a^m , b^m , and c^m define the quadratic cost function of the DG [167], and $P_{DG}^m(t)$ denotes the output power of the DG unit of the m^{th} MG. Constraint (7.3) maintains the acceptable minimum and maximum power output levels of the DG unit ($[P_{DG}^{min,m}, P_{DG}^{max,m}]$). Also, (7.4) enforces the Generation Rate Constraint (GRC) of the DG unit. In this paper, H , t , and Δt denote the length of the decision window, time instant, and decision time step value, respectively. The

apparent power of the DG, \mathbf{S}_{DG}^m , is defined in (7.5) as a function of the DG's active and reactive power ($\mathbf{Q}_{DG}^m(\mathbf{t})$) and is maintained within its boundaries ($[\mathbf{0}, \mathbf{S}_{DG}^{max,m}]$) through (7.6). To enforce the local voltage constraint (7.7) on the DG's bus voltage magnitude ($|\mathbf{V}_{DG}^m(\mathbf{t})|$), a convex relaxation of AC power flow is adopted from [77] and shown in (7.8). This procedure is used for other micro-sources as well. The convexity of the constraints is crucial to ensure that the NBS is well-defined [132]. Here, \mathcal{N}_{DG} denotes the set of neighboring buses to the DG bus. $\mathbf{R}_{DG,j}$ and $\mathbf{X}_{DG,j}$ are the resistance and reactance values of the line connecting the DG bus to its j^{th} neighboring bus, respectively. Also, $\mathbf{P}_{DG,j}$ and $\mathbf{Q}_{DG,j}$ define the active and reactive power sent from the DG to its j^{th} neighboring bus. Other convex relaxations of the AC power flow found in the literature (e.g., [23] [162]) can also be used in the decision problem.

- DR provider agent:

$$U_{1,2}^m = \frac{1}{H} \cdot \sum_{t=1}^H \{ \lambda_R(t) \cdot P_f^m(t) \cdot (1 - e^{-\omega^m(P_f^m(t) - P_C^m(t))}) \} \quad (7.9)$$

$$U_{2,2}^m = \sum_{t=1}^H \{ -P_C^m(t) \lambda_R(t) \} \quad (7.10)$$

$$P_C^{min,m} \leq P_C^m(t) \leq P_C^{max,m} \quad (7.11)$$

$U_{1,2}^m$ and $U_{2,2}^m$ represent penalty for load reduction [60], and cost-savings, respectively, as two competing objective functions for DR management. Thus, deviations from the target (forecasted) fixed load value ($P_f^m(t)$) are penalized through $U_{1,2}^m$, depending on the aggregate participation factor, ω^m . $P_C^m(t)$ defines the aggregate power of the curtailed load, and $[P_C^{min,m}, P_C^{max,m}]$ are the acceptable curtailment boundaries of the DR resources.

- ESS control agent:

$$P_{ESS}^{min,m} \leq P_{ESS}^m(t) \leq P_{ESS}^{max,m} \quad (7.12)$$

$$SOC^m(t) = SOC^m(t-1) - \frac{\Delta t}{E_{max,m}} \cdot P_{ESS}^m(t) \quad (7.13)$$

$$SOC^{min,m} \leq SOC^m(t) \leq SOC^{max,m} \quad (7.14)$$

$$S_{ESS}^m(t) = \sqrt{(P_{ESS}^m(t))^2 + (Q_{ESS}^m(t))^2} \quad (7.15)$$

$$S_{ESS}^{min,m} \leq S_{ESS}^m(t) \leq S_{ESS}^{max,m} \quad (7.16)$$

$$V_{ESS}^{min,m} \leq |V_{ESS}^m(t)| \leq V_{ESS}^{max,m} \quad (7.17)$$

$$|V_{ESS}^m(t)| \approx 1 + \sum_{j \in \mathcal{N}_{ESS}} \{R_{ESS,j} P_{ESS,j} + X_{ESS,j} Q_{ESS,j}\} \quad (7.18)$$

the ESS control agents need to enforce constraints (7.12)-(7.18), where, (7.12) defines the minimum/maximum limits ($[P_{ESS}^{min,m}, P_{ESS}^{max,m}]$) on the output power of the ESS unit ($P_{ESS}^m(t)$). Also, (7.13) and (7.14) describe the State Of Charge (SOC) computation and limitations ($[SOC^{min,m}, SOC^{max,m}]$) of the ESS, with $E_{max,m}$ denoting the nominal energy capacity of the battery system in the m^{th} MG. Equations (7.15)-(7.18) enforce the local apparent power (S_{ESS}^m) and voltage magnitude ($|V_{ESS}^m(t)|$) constraints of the ESS, similar to the DG unit (with Q_{ESS}^m denoting the output reactive power of the ESS).

- **PV control agent:**

As discussed previously, the goal of the PV control agent is to maintain the local voltage and apparent power constraints of the PV bus, as follows:

$$S_{PV}^m(t) = \sqrt{(P_{PV}^m(t))^2 + (Q_{PV}^m(t))^2} \quad (7.19)$$

$$S_{PV}^{min,m} \leq S_{PV}^m(t) \leq S_{PV}^{max,m} \quad (7.20)$$

$$V_{PV}^{min,m} \leq |V_{PV}^m(t)| \leq V_{PV}^{max,m} \quad (7.21)$$

$$|V_{PV}^m(t)| \approx 1 + \sum_{j \in \mathcal{N}_{PV}} \{R_{PV,j} P_{PV,j} + X_{PV,j} Q_{PV,j}\} \quad (7.22)$$

where, P_{PV}^m , Q_{PV}^m , and S_{PV}^m denote the active, reactive, and apparent output power of the PV system. Note that based on our assumption of maximum power point tracking for the PV system, P_{PV}^m is an input to the decision problem at different time steps. The constraints on the voltage of the PV bus (V_{PV}^m) are shown in (7.21) and (7.22), similar to the DG unit.

- **Main MG control agent at the PCC:**

$$U_{1,3}^m = \sum_{t=1}^H \{-(P_G^m(t))^2\} \quad (7.23)$$

$$P_G^{min,m} \leq P_G^m(t) \leq P_G^{max,m} \quad (7.24)$$

$$P_{Ex}^{max} \leq \sum_{m=1}^M P_G^m(t) \leq P_{Im}^{max} \quad (7.25)$$

$U_{1,3}^m$ is the objective function for the main MG agent (of the m^{th} MG). Its function is to promote self-sufficiency and avoid over-loading and congestion at the MG's PCC [174]. Constraint (7.24) defines the physical congestion limits of the m^{th} MG at the PCC ($[P_G^{min,m}, P_G^{max,m}]$). The system-wide power balance constraint is considered through (7.25), where P_{Ex}^{max} and P_{Im}^{max} define the maximum power export and import limits to the utility company, and M denotes the number of MGs in the Regional Energy Network (REN). Note that (7.25) only appears in the decision problem of the main MG agents at the PCC, which implies that the control agents of the micro-sources of the different MGs do not need to be connected together through communication links (only the control agents of the micro-sources within each MG are connected locally to their peers.)

Apart from the introduced constraints, all the control agents of each MG need to enforce the local MG-wide power balance constraint in their decision model:

$$P_{DG}^m(t) + P_{PV}^m(t) + P_{ESS}^m(t) + P_G^m(t) + P_C^m(t) = P_f^m(t) \quad (7.26)$$

where, $P_f^m(t)$ is uncontrollable load level for the m^{th} MG. The overall cooperative resource allocation problem can be cast as NBS, as shown in our previous work [46]:

$$\max_{\mathbf{P}, \mathbf{Q}} \left\{ \sum_{m=1}^M \sum_{i=1}^{N_m} \log \left(\prod_{j=1}^{O_i^m} (U_{j,i}^m - d_{j,i}^m) \right) \right\}, \quad (7.27)$$

$$s.t. \text{ (7.3) - (7.8), (7.11) - (7.22), (7.24) - (7.26) } \forall m$$

where, \mathbf{P} and \mathbf{Q} are the decision vectors, containing the active and reactive power outputs of all controllable resources. N_m denotes the number of control agents of the m^{th} MG and O_i^m defines the number of objective functions of the i^{th} control agent in the m^{th} MG. Also, $d_{j,i}^m$'s represent the disagreement points of the bargaining process

(i.e., worst case scenarios). The DSGA can be employed to solve (7.27) through a distributed optimization framework, as demonstrated in our previous work [46], and in [149] [150].

Making the Distributed Bargaining Framework Resiliency-Aware

To introduce resiliency-awareness into the distributed optimization framework, we introduce a new objective function into the optimization problem (7.27). This objective function can be handled by a separate agent in each MG or the main control agent of every MG. The basic premise of this objective function is to minimize the expected power deficiency in case the MGs become islanded due to an extreme event, or if there is a unit failure in the system. Hence, we assume that an expert system or a forecasting unit is present at each MG to estimate the probability of MG islanding during extreme weather events. This probabilistic value can also be given as an input by the MG owners/operators. For instance, if there is an upcoming extreme event such as a hurricane or a storm in the area, the forecasting unit will assign a higher probability to the islanding scenario of the MGs since there is higher chance that a blackout will occur in the main grid. These probabilities can be estimated using statistical history of the system [157] and environmental parameters. Also, note that these probability values are time-varying, and change based on the state of the environment and weather.

Given these estimated probability values, different system configurations, consisting of component failure scenarios, shown in Fig. 7.2, can be defined for each MG, as follows:

$$P\{C_i\} = \prod_{j=1}^{e_{C_i}} P\{E_j\} \quad (7.28)$$

where, C_i denotes the i^{th} configuration, and E_j is an event belonging to the

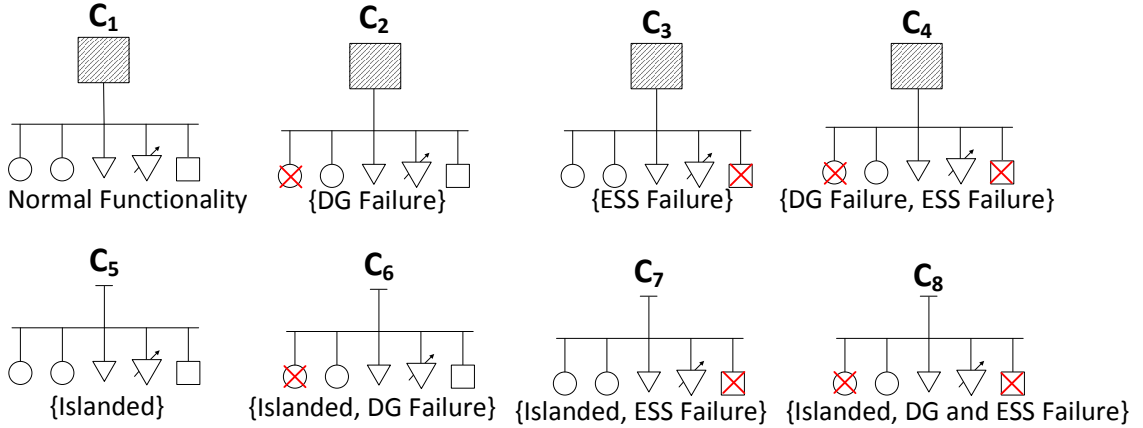


Figure 7.2: Different probable configurations for each MG, due to islanding and unit failure

configuration's event set (consisting of e_{C_i} events). Also, $P\{\cdot\}$ defines the probability values of events/configurations. Since, each MG is a small-scale power system enumerating all the configurations is not numerically expensive. In this paper, we consider the following event set for each MG: {MG islanding, DG failure, ESS failure}. The probability set corresponding to this event set is defined (for the m^{th} MG) as: $\{p_{is}^m(t), p_{dg}^m(t), p_{ess}^m(t)\}$. Hence, there are eight possible system configurations for each MG (Fig. 7.2), with probability values defined as: $\{p_{C_1}^m(t), \dots, p_{C_{c_{max}}}^m(t)\}$, where c_{max} denotes the maximum number of configurations. Note that we have assumed that these events are statistically independent from each other. Given this probabilistic view of the system configurations, the objective function for improving system resiliency is defined as follows:

$$U_{2,3}^m = - \sum_{t=1}^H \sum_{i=1}^{c_{max}} \{(P_{Def}^m(t, C_i) - P_{Res}^m(t, C_i)) \cdot p_{C_i}^m(t)\} \quad (7.29)$$

where, $P_{Def}^m(t, C_i)$ and $P_{Res}^m(t, C_i)$ are the immediate power deficit level and total available power reserve at time t under system configuration C_i , for the m^{th}

MG, respectively. Hence, through (7.29) the expected value of net power deficit is minimized. The main elements of this objective function are defined as follows:

$$\begin{aligned} P_{Def}^m(t, C_i) = & r\{P_f^m(t) - P_{DG}^m(t, C_i) - P_{PV}^m(t) \\ & - P_{ESS}^m(t, C_i) - P_G^m(t, C_i) - P_C^m(t)\} \end{aligned} \quad (7.30)$$

$$\begin{aligned} P_{Res}^m(t, C_i) = & P_{DG,Res}^m(t, C_i) + P_{G,Res}^m(t, C_i) \\ & + P_{ESS,Res}^m(t, C_i) + P_{C,Res}^m(t) \end{aligned} \quad (7.31)$$

where, $r\{\cdot\}$ is the ramp function (i.e., $r(x) = x$ for $x \geq 0$ and $r(x) = 0$ otherwise). Also, $P_{DG,Res}^m(t, C_i)$, $P_{G,Res}^m(t, C_i)$, $P_{ESS,Res}^m(t, C_i)$, and $P_{C,Res}^m(t)$ define the available power reserve from the different micro-sources of each MG at different times and for different configurations. For each micro-source, the reserve level is a function of the operating point, and power and energy capacity of the source:

$$P_{DG,Res}^m(t, C_i) = \min(P_{DG}^{max,m} - P_{DG}^m(t, C_i), GRC^m \cdot \Delta t) \quad (7.32)$$

$$P_{G,Res}^m(t, C_i) = P_G^{max,m} - P_G^m(t, C_i) \quad (7.33)$$

$$\begin{aligned} P_{ESS,Res}^m(t, C_i) = & \min(P_{ESS}^{max,m} - P_{ESS}^m(t, C_i), \\ & \frac{E(t, C_i) - E^{min,m}}{\Delta t}) \end{aligned} \quad (7.34)$$

$$P_{C,Res}^m(t, C_i) = P_C^{max,m} - P_C^m(t) \quad (7.35)$$

where, the $\mathbf{min}(a, b)$ operator selects the smaller number among its operands. $E(t, C_i)$ and $E^{min,m}$ denote the available and minimum allowable energy levels of the ESS unit (i.e., SOC), respectively. Note that based on (7.32) the available reserve from the DG is limited by its ramp rate constraint and maximum power capacity. Also, the reserve from the ESS unit is constrained by its maximum power capacity and minimum SOC limit, as can be seen in (7.34).

Considering (7.30)-(7.35), we observe that the objective function (7.29) is not differentiable at all points in the decision space. Hence, gradient cannot be obtained at these points. An advantage of the DSGA algorithm is that the technique still works for these types of non-differentiable functions simply by replacing gradient with sub-gradient, which exists at all points for the introduced objective function [150].

For the micro-sources that are present in configuration C_i (whose power we denote with $P_{MS}^m(t, C_i)$) and are able to contribute to system resiliency we have:

$$\begin{aligned} \frac{\partial P_{Def}^m(t, C_i)}{\partial P_{MS}^m(t, C_i)} = & \mathbb{1}\{P_f^m(t) \geq P_{DG}^m(t, C_i) + P_{PV}^m(t) \\ & + P_{ESS}^m(t, C_i) + P_G^m(t, C_i) + P_C^m(t)\} \end{aligned} \quad (7.36)$$

where, $\mathbb{1}\{\cdot\}$ is the indicator function with respect to input S , defined as follows:

$$\mathbb{1}\{S\} = \begin{cases} 1 & \text{if } S \text{ is True} \\ 0 & \text{if } S \text{ is False} \end{cases} \quad (7.37)$$

Note that the sub-derivative (7.36) basically states that the remaining micro-sources in a certain configuration should increase their output power to compensate

for power deficiency in generation outage, ESS failure, or islanding scenarios. Using the indicator function and the simple fact that $\min(\mathbf{a}, \mathbf{b}) = \frac{1}{2}(\mathbf{a} + \mathbf{b} - |\mathbf{a} - \mathbf{b}|)$, the sub-derivatives of power reserve with respect to different decision variables can be calculated from equations (7.32)-(7.35), as:

$$\frac{\partial P_{DG,Res}^m(t, C_i)}{\partial P_{DG}^m(t, C_i)} = -\mathbb{1}\{P_{DG}^{max,m} - P_{DG}^m(t, C_i) \leq GRC^m \cdot \Delta t\} \quad (7.38)$$

$$\frac{\partial P_{G,Res}^m(t, C_i)}{\partial P_G^m(t, C_i)} = -1 \quad (7.39)$$

$$\frac{\partial P_{C,Res}^m(t, C_i)}{\partial P_C^m(t, C_i)} = -1 \quad (7.40)$$

$$\frac{\partial P_{ESS,Res}^m(t, C_i)}{\partial P_{ESS}^m(t, C_i)} = -1 \quad (7.41)$$

$$\frac{\partial P_{ESS,Res}^m(t, C_i)}{\partial P_{ESS}^m(t', C_i)} = -\mathbb{1}\{P_{ESS}^{max,m} - P_{ESS}^m(t, C_i) \geq \frac{E(t, C_i) - E^{min,m}}{\Delta t}\}, \quad (for\ t' < t) \quad (7.42)$$

Intuitively, equations (7.38)-(7.42) tend to prevent the micro-sources from being deployed up to their full capacity, in order to make room for sufficient power reserve in case there is an emergency.

Using equations (7.36) along with (7.38)-(7.42), we obtain the total sub-gradient of objective function (7.29) with respect to the decision vector \mathbf{P} in (7.27). This sub-gradient is then inserted in the DSGA to complete the algorithm.

Simulation Results and Discussion

The proposed power management model is tested on a distribution system consisting of three MGs, with each MG being a modified version of the IEEE 13-bus standard distribution network used in our previous work [45]. Note that the MGs are not identical, and have micro-sources with different nominal capacities and outputs, as in [46]. PV power profiles of the MGs have been obtained from [59], and shown in Fig. 7.3. Fig. 7.4 shows the fixed load data for the MGs, which are adopted from [152] and [83]. In this paper, the retail price is assumed to be \$90/MWh at all times of the day.

Three case studies are considered: in Case I, the behavior of MGs is investigated when a blackout in the main grid is expected due to high probability of an extreme event. In Case II, a high failure probability is assigned to a DG unit in one of the MGs for a certain time period and the reaction of the power management strategy to the probable unit failure scenario is investigated. Hence, in both of these cases, the power management predicts how to “prepare” the system for a certain look-ahead time in the pre-event state, based on the forecasted probabilities for the occurrence of different events (e.g., islanding or unit failure). In Case III, the behavior of an islanded MG under ESS failure scenario is studied, with a focus on the load voltage profile.

Case I: Probable Grid Blackout Due to an Extreme Event

In Fig. 7.5, the estimated islanding probability of the MGs is shown during a certain time interval of day for two scenarios. These probability values are estimated by the expert system or given as input to the optimization problem by the owner/operator of each MG, as described in Section III. As can be seen in this

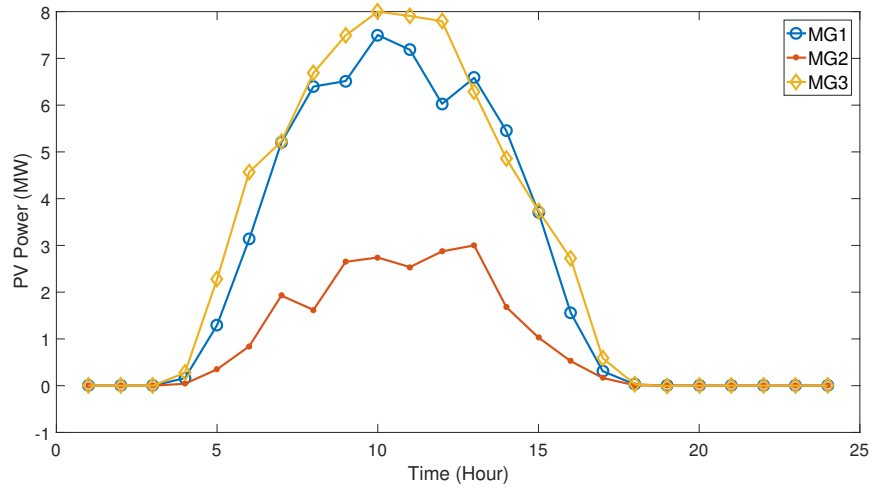


Figure 7.3: PV power data for different MGs

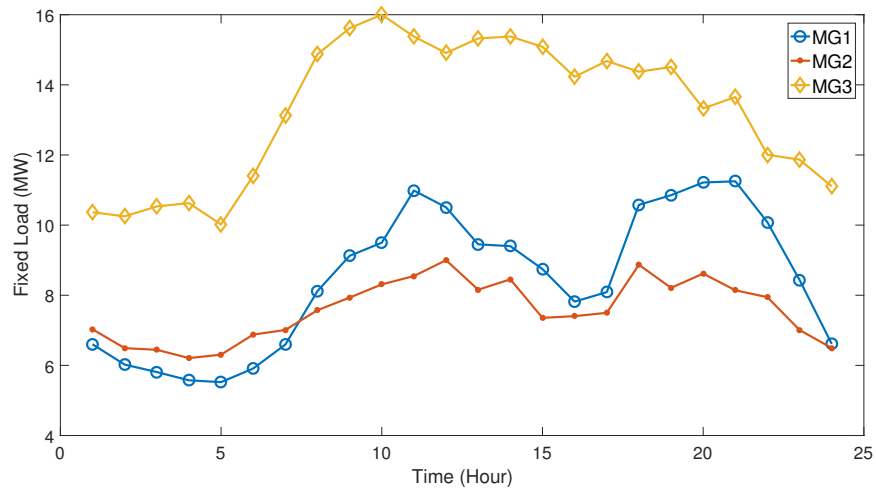


Figure 7.4: Fixed load profiles of different MGs

figure, at the time interval 16:00-21:00, the probability of islanding jumps to 0.3 in one scenario (mild possibility of grid blackout), and to 0.9 in another scenario (severe possibility of disruption with almost certain blackout in the main grid). The distributed optimization framework has been run under these two scenarios. The improvement levels in the expected loss of load (compared to the case where resiliency-awareness is not built into the decision model) are shown in Fig. 7.6. As is shown in this figure, the percentage improvement level in expected loss of load is considerably higher as the probability of islanding increases. This implies higher levels of self-sufficiency in operation of the MGs during islanding.

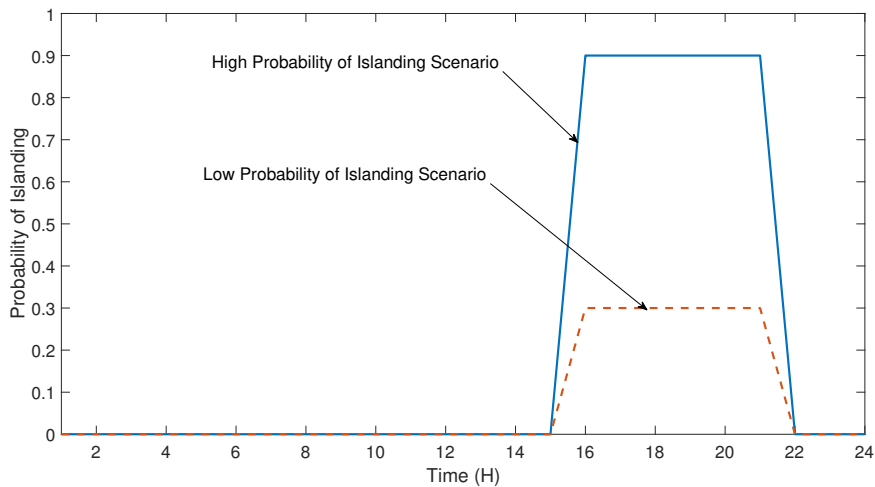


Figure 7.5: Probability of MG islanding

To verify the performance of the resiliency-aware distributed power management scheme it is crucial to compare the performance of the system with and without the proposed objective function. Hence, tests have been run for these two cases, where in both cases an islanding probability of 0.9 is forecasted for time interval 16:00-21:00 for all the three MGs (as shown in Fig. 7.5). The value of total reserve from the micro-sources of all the three MGs is shown in Fig. 7.7. As can be seen in this figure,

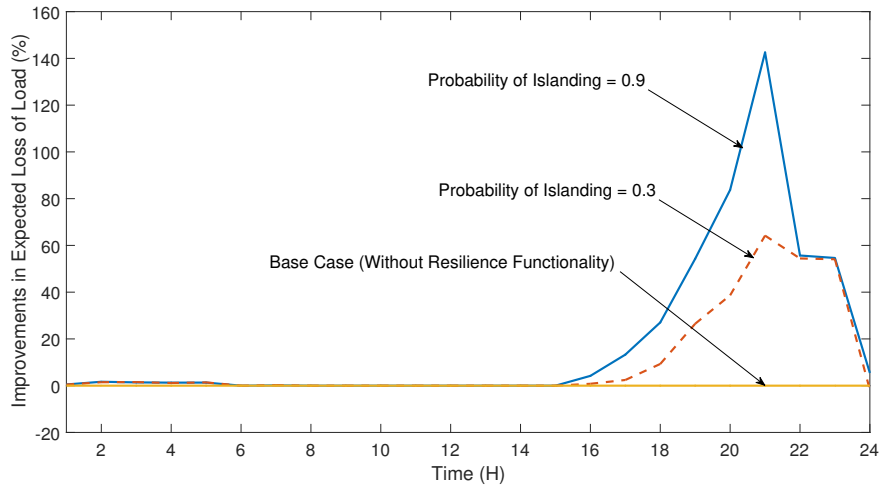


Figure 7.6: Improvements in the expected power deficit under different islanding scenarios

when the resiliency-aware functionality is built into the power management system, higher reserve values are maintained during the times that islanding is expected.

A significant portion of the higher power reserve during the higher probability of extreme event (islanding) is due to change in operation of ESS units of the MGs. In Fig. 7.8, the total stored energy level of all the ESS units in the distribution system is shown at different times of day. It can be observed, that employing the resiliency-aware functionality leads to higher stored energy levels, especially at critical times of day, when higher chances of islanding is expected. Note that higher stored energy implies higher available power reserve levels.

Another interesting aspect of the system operation with the resiliency-aware functionality is that introducing the proposed objective function leads to lower power export to the grid during the critical time interval 16:00-21:00 to prepare for islanding, as demonstrated in Fig. 7.9. This reduction in the export is due to higher concentration on reserve allocation, which leads to reduced reliance on the grid. On the other hand, lower power export to the grid leads to a loss of revenue for the

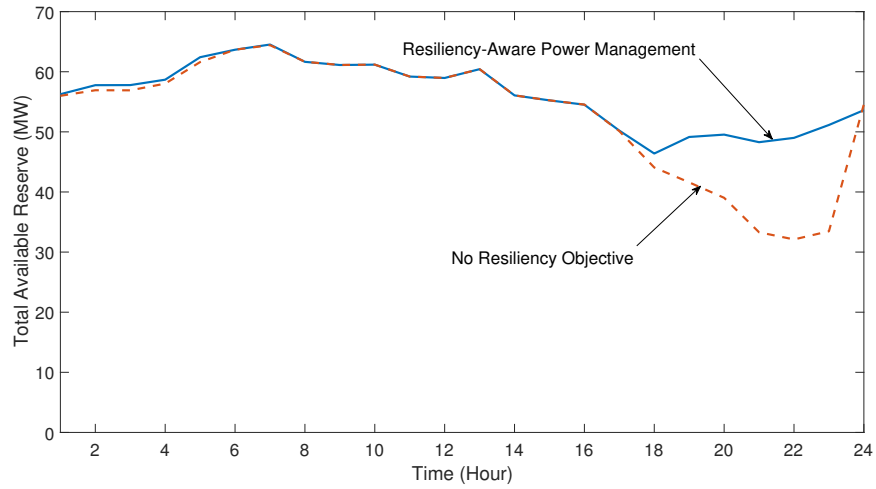


Figure 7.7: Reserve allocation with and without resiliency-aware functionality

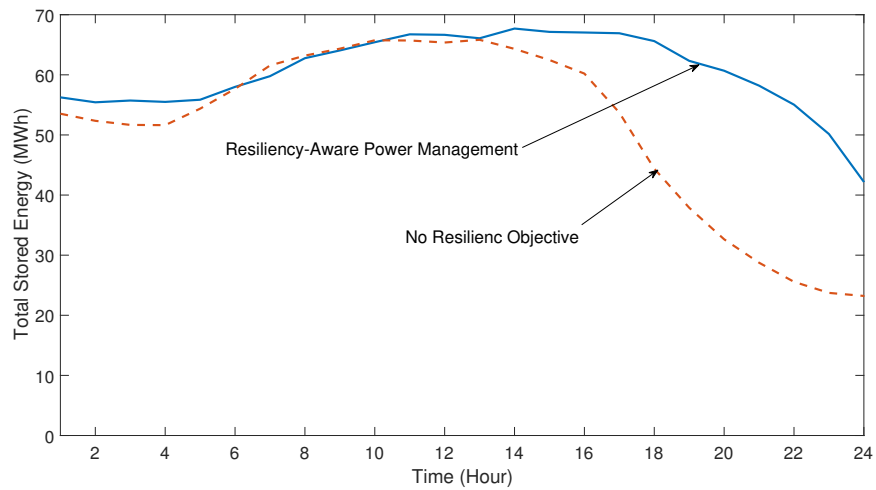


Figure 7.8: Total stored energy in the ESS units within the MGs

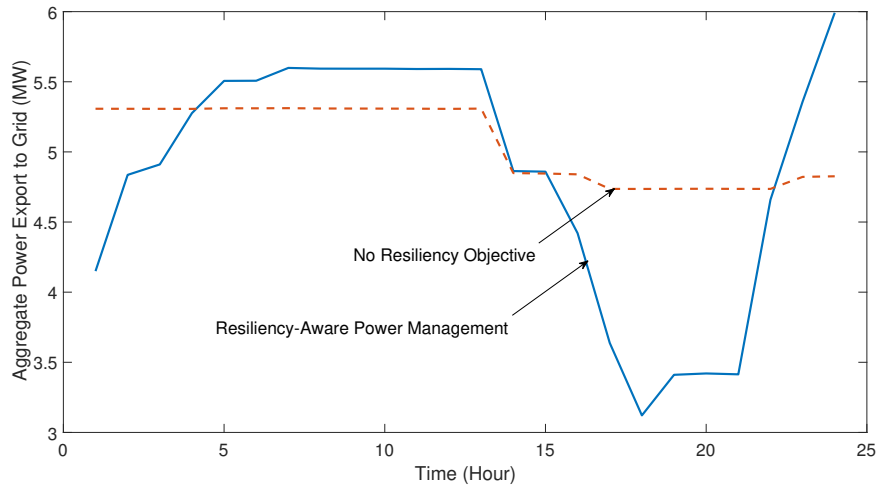


Figure 7.9: Total power export to the main grid

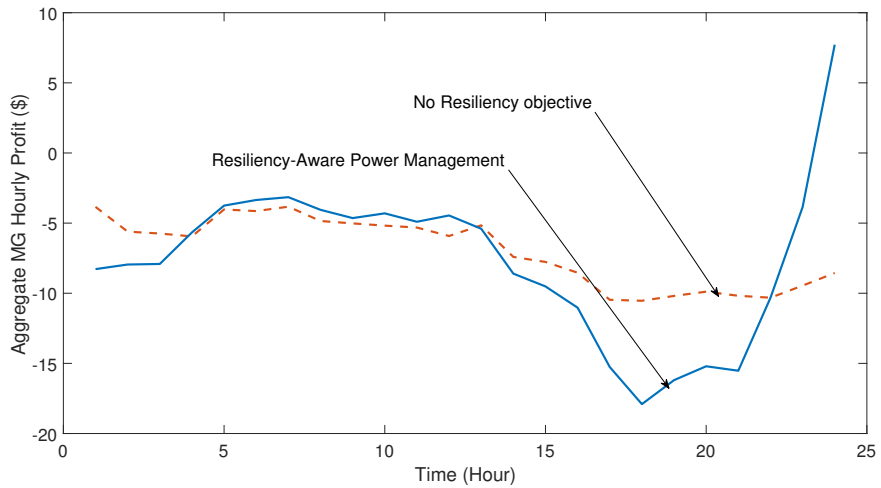


Figure 7.10: Hourly profit level of all MGs through sales of power to the grid

MGs, which is usually not the focus at times of crisis. Fig. 7.10 shows the aggregate hourly profit of the MGs with and without the resiliency-aware functionality. As is demonstrated here, resiliency-awareness leads to a decrease in the profit level, at the time interval where a blackout in the main grid is expected. The total loss of profit is equal to 9.3% compared to the base case without the proposed objective function. This suggests that there is a trade-off between the two objective functions of resiliency-awareness and short term profit.

Case II: Probable Unit Failure Scenario

In Case I, we assigned a near-zero probability to unit failure events. For Case II, we assume that the DG unit in MG1 has a high probability of failure (equal to 0.9) during the peak load hours 18:00-22:00 (Fig. 7.4). The power profile of the DG unit for MG1, with and without the resiliency functionality, is shown in Fig. 7.11. As can be seen in this figure, introducing the resiliency-aware functionality leads to significant drop in the DG unit output power during the critical time interval, when the failure is expected. Due to the decreased power output from the DG unit, MG1 needs to rely on other MGs and the main grid to maintain the local load balance. The aggregate hourly power export profile of the MGs to the main grid is shown in Fig. 7.12. As is observed in this figure, for the case with resiliency-aware functionality, MGs start buying (importing) power from the main grid during the critical time interval to compensate for the lower power output from the DG unit of MG1, as expected. For the case without resiliency-aware functionality, power export from the MGs to the grid continues during the critical time interval. Hence, we can conclude that the inclusion of the proposed objective function (7.29) in the power management algorithm is able to prepare the MGs for expected (predicted) unit failure events, by changing the output power of the micro-sources in favor of the healthier units.

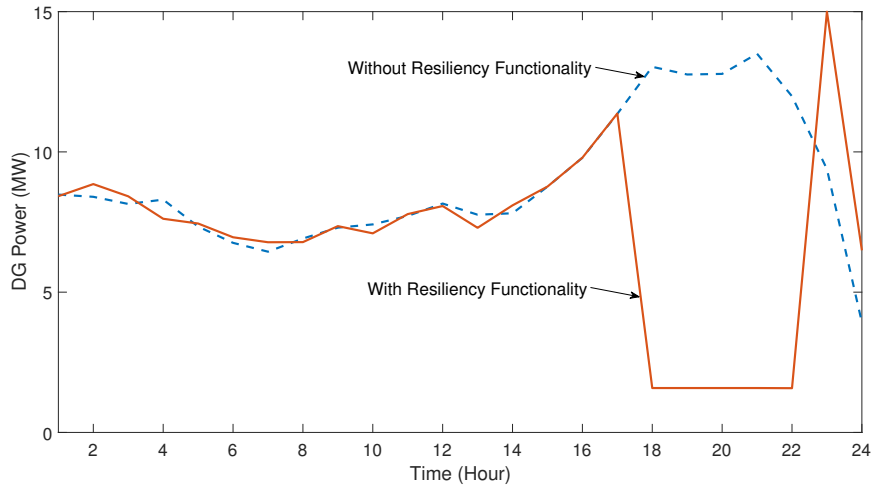


Figure 7.11: Hourly power output of MG1's DG unit

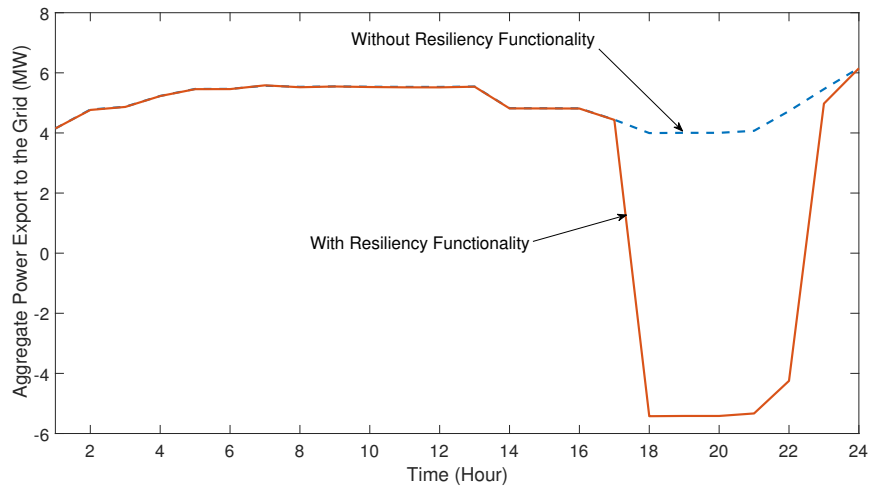


Figure 7.12: MGs' power export to the grid

Case III: Islanding and Unit Failure Scenario

In this section we study the behavior of islanded MG1 with healthy units and under a unit failure scenario. The voltage profile of the islanded MG without unit failure is shown in Fig. 7.13. As can be seen in this figure the voltage level of all the micro-source buses are kept within permissible bounds (1 ± 0.05 p.u) at all times. Now we assume an ESS unit failure occurs at time 9:00, as shown in Fig. 7.14.

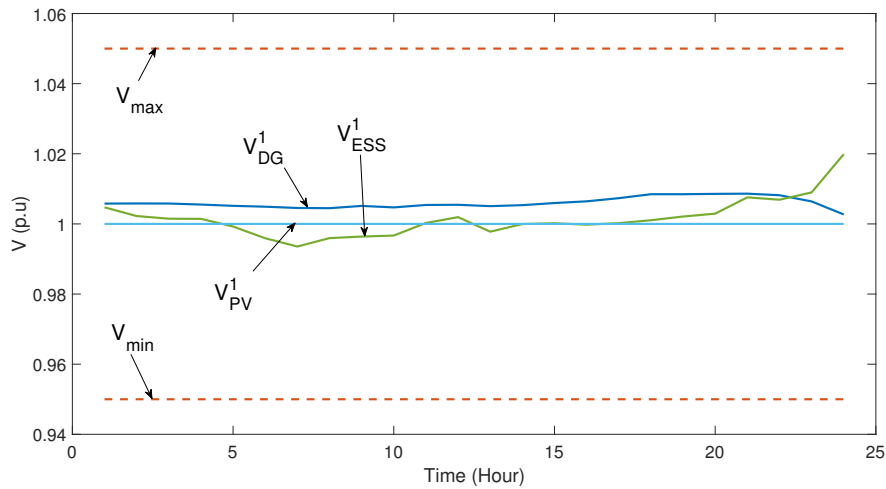


Figure 7.13: Voltage magnitude of micro-source buses

Initially, the DG unit along with the PV system are able to supply the MG load and maintain the system power balance by load following, as observed in Fig. 7.15. However, during the later hours of the day (17:00-22:00) when a secondary peak occurs in the load profile of MG1, (Fig. 7.4), and PV power is not available, the DG unit alone is not able to maintain the power balance in the system. As can be seen in Fig. 7.15, the DG output power reaches its maximum level, indicating that the total reserve from the micro-sources is exploited. To maintain the power balance in this interval, DR resources are employed as depicted in Fig. 7.16. This case shows the use of limited load shedding during critical time intervals, when power reserve is

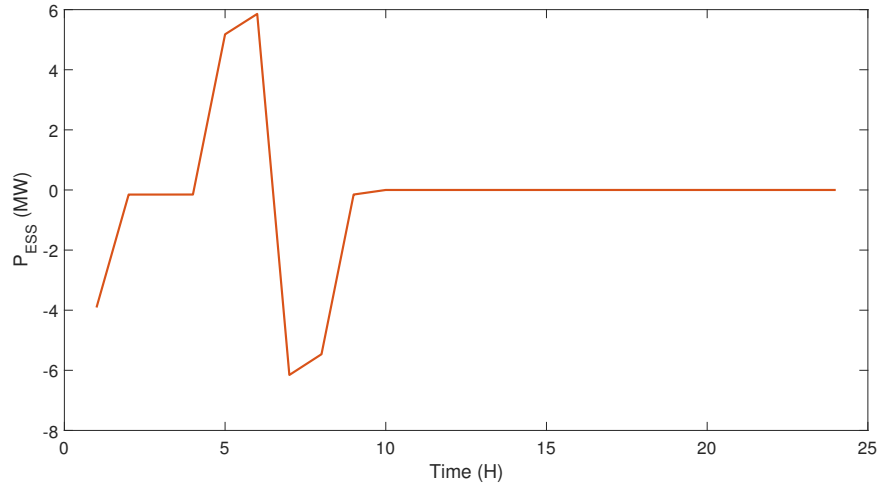


Figure 7.14: ESS output power under failure scenario

not available in the system from local generation units.

The employment of DR resources has a direct effect on the voltage profile at the load bus in which DR resources are available. As depicted in Fig. 7.17, without using DR resources the voltage of the load feeder drops below the minimum permissible limit, during the critical peak load interval, while the employment of DR resources keeps the bus voltage within the limits.

Conclusion

In this paper, We have proposed a resiliency-aware power management approach, to prepare the system for extreme events and unit failure, considering multiple MGs in a power distribution network. The proposed agent-based method is based on a fully distributed cooperative resource allocation scheme which attempts to maintain bus voltages within the permissible limit. NBS is used as a solution concept for the decision model. To improve the resiliency of the system, a probabilistic objective function is introduced into the cooperative reserve allocation problem of the MGs,

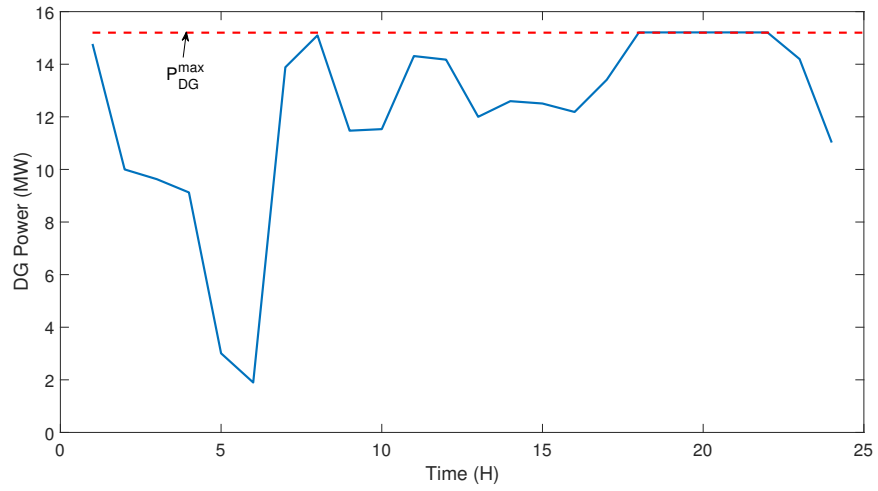


Figure 7.15: DG unit output power under ESS failure scenario

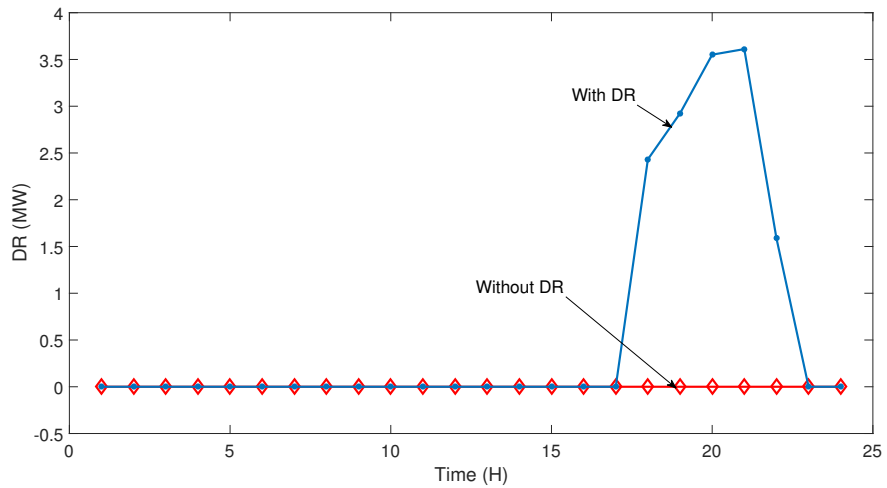


Figure 7.16: Employed DR resource power under ESS failure scenario

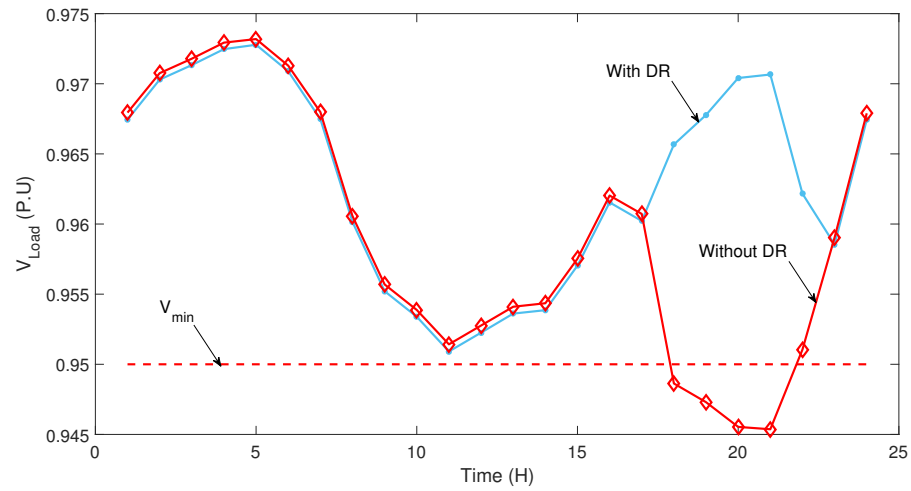


Figure 7.17: Load voltage profile

which minimizes the expected net power deficit for each MG and prepares the system for improved performance during expected extreme events. The numerical results show that the proposed model is able to reduce the power deficit during critical times and contribute to the resiliency of the system.

CONCLUSION

In this dissertation the problem of distributed agent-based optimal resource allocation in power systems has been investigated. While in the second chapter decision making in wholesale markets has been addressed, the remaining chapters focus on the retail sector. More significantly, in this work we have developed a market-based framework for power management and optimal dispatching of resources in the electric distribution systems, including MGs. The problem of coordinating the response of multiple MGs, under normal and abnormal conditions (e.g., islanding scenarios under extreme events) have been investigated. The following conclusions have been reached based on the studies presented in this dissertation, and provide a summary of the major contributions of this work:

- The two important parts of game theoretic solution concepts, NE and NBS, are used to design resource allocation mechanisms in power systems. NE is employed to describe the stable equilibrium of wholesale markets and model GenCo competition. Employing NBS, a unique, fair, and Pareto-optimal solution strategy is used to solve the cooperative power management problem of single and multiple MGs. Furthermore, NBS can be obtained in a distributed agent-based fashion, which results into a modular automation system without a single point of failure. Different operational constraints (including line power flow and bus voltage constraints) can be integrated into the decision model.
- Using probabilistic decision tools at the wholesale level, GenCos can accurately predict the Nash equilibrium of the market and maximize their profit by performing optimal response strategy to competitors. The use of the probabilistic DBN-based decision tool has been studied in bi-level optimization market models at different time stages (DA, HA, and RT).

- Employing an iterative machine-learning-based framework, a retailer agent (e.g., utility company) is enabled to perform optimal dynamic retail pricing under incomplete information (i.e., without having direct access to participants' private dataset). Using the introduced pricing mechanism, the utility company is able to pursue various objectives, such as DA profit maximization, peak reduction, and RT cost minimization. This market structure has been successfully tested for different types of participants, including residential AC loads as DR providers and multiple MGs. The numerical results from the proposed dynamic pricing scheme show that dynamic pricing leads to higher correlation among retail and wholesale sectors. Also, the effect of disturbances in RT can be neutralized and minimized by sending the proper price signal to MGs. In other words, employing a market-based framework the potentials of active distribution systems can be realized to the society's advantage.
- Using a probabilistic view of the system, the operation of MGs can be modified to enhance the resiliency of the distribution system by preparing it against the effects of extreme events, through reserve allocation.

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