Fall 2022

MULTI-STAGE MULTI-MARKET OPTIMAL BIDDING STRATEGY IN ELECTRICITY MARKETS

Hossein Mehdipourpicha
Missouri University of Science and Technology

Department: Electrical and Computer Engineering

MULTI-STAGE MULTI-MARKET OPTIMAL BIDDING STRATEGY IN

ELECTRICITY MARKETS

by

HOSSEIN MEHDIPOURPICHA

A DISSERTATION

Presented to the Graduate Faculty of the

MISSOURI UNIVERSITY OF SCIENCE AND TECHNOLOGY

In Partial Fulfillment of the Requirements for the Degree

DOCTOR OF PHILOSOPHY

in

ELECTRICAL ENGINEERING

2022

Approved by:

Dr. Rui Bo, Advisor
Dr. Ahmad Alsharoa
Dr. Jiangfan Zhang
Dr. Yanjie Fu
Dr. Yishu Zhou

ABSTRACT

Restructuring of power industry created the competitive situations for different MPs through designing appropriate electricity markets. Typically, in pool-based electricity markets, MPs submit their offers, and ISO clears the market and notifies MPs of the cleared power amounts and market prices. In this situation, designing an effective bidding strategy for MPs who seek to maximize their profits has thus become one of the crucial yet difficult tasks that still need further exploration. The majority of recent studies overlooked this problem for the purely financial players. Therefore, designing an efficient strategy for virtual bidder in the pool-based electricity markets is studied in this work. Moreover, this problem is extensively examined for the asset-owned MPs who are able to place virtual bids into the electricity market and the difference between the behavior of this player and the virtual bidder's decision is highlighted employing different case studies. Transmission congestion in power system causes the price separation in different nodes in the DA electricity market, which creates the difference between the payment to the generators and the payment collected from the loads. ISO, as a nonbeneficiary organization, redistributes this surplus to the MPs through the FTR auction. The FTR value is dependent to the DA LMP. That is, the DA market and FTR auction are interrelated from a MP's viewpoint. Furthermore, a strategic MP may tend to manipulate the FTR value employing the virtual transactions to improve its overall strategy in participating in both FTR auction and DA market. Therefore, this work also proposes a bidding strategy framework for a price-maker MP attending in both FTR auction and DA market with the consideration of virtual bidding.

ACKNOWLEDGMENTS

I would like to thank my adviser, Dr. Rui Bo, for his ongoing advice and support throughout my PhD studies as well as my student life. I am grateful for his commitment to mentoring, tutoring, and assisting me in this period.

I also appreciate the contributions and comments made by the committee members, Dr. Ahmad Alsharoa, Dr. Jiangfan Zhang, Dr. Yanjie Fu, and Dr. Yishu Zhou on this work. Thanks to all students in the Missouri S&T Power System Lab. Their friendship, encouragement, and help were indeed beneficial to my study and research work.

Last but not least, I owe a huge debt of gratitude to my wife, Niloofar Zendehdel, for her endless love and unconditional support, which enabled me to complete this work. I would like to sincerely dedicate this dissertation to her.

TABLE OF CONTENTS

Page

LIST OF ILLUSTRATIONS

LIST OF TABLES

Page

NOMENCLATURE

Symbol	Description
t	Index for time periods
v	Index for virtual bids
i	Index for strategic generating units
c	Index for FTR sellers
e	Index for strategic FTR buyer
j	Index for other generating units
f	Index for other FTR buyers
b	Index for generation blocks
d	Index for demands
k	Index for demand blocks
l	Index for lines
n	Index for buses
m	Index for FTR paths
$sink, source$	Index for Sink and Source buses
N_{pur}, N_{sell}	Set of sellers and buyers in the FTR auction
Ω_1^{FTR}	Set of decision variables in UL of FTR auction model
Ω_2^{FTR}	Set of decision variables in LL of FTR auction model
Ω_1^{DA}	Set of decision variables in UL of DA market model
Ω_2^{DA}	Set of decision variables in LL of DA market model

$\overline{FTR}_e^S$	Upper limit of FTR for strategic FTR buyer *e*
$\overline{FTR}_f$	Upper limit of FTR for other FTR buyer *f*
$\overline{FTR}_c$	Upper limit of FTR for FTR seller *c*
σ_c	Offer price of FTR seller *c*
ρ_f	Bid price of FTR buyer *f*
H_{lm}	Sensitivity of line *l* to the FTR MW in path *m*
λ_{tn}^{RT}	Real-Time locational marginal price at time t and bus n
λ_{tib}^{S}	Marginal cost of unit i of the strategic generator at time t
$\bar{P}_{tib}^{S}$	Upper power limit of unit i of the strategic generator at time t
$\bar{P}_{tjb}^{G}$	Upper power limit of unit j of other generators at time t
$\bar{P}_{tdk}^{D}$	Upper power limit of demand d at time t
λ_{tjb}^{g}	Marginal cost of unit j of other generators at time t
λ_{tdk}^{d}	Marginal utility of demand d of the at time t
V_{tv}^{budget}	Upper quantity limit of virtual bid v at time t
$\bar{F}_l$	Line l Capacity
$PTDF_{nl}$	Power Transfer Distribution Factor
R_i^{UP}, R_i^{LO}	Ramp-up and ramp-down limits for strategic unit i
FTR_e^{Sbid}	Bid quantity for FTR bidder e
FTR_e^{s}	Cleared quantity for FTR bidder e
FTR_c	Cleared FTR for seller c

FTR_f	Cleared FTR for buyer f
ρ_e^s	Bid price for FTR bidder e
LF_l	Power flow in line l in FTR auction
F_l	Power flow in line l in DA market
P_{tib}^{Sbid}	Bid power of the strategic generating unit i at time t
P_{tib}^{S}	Cleared power of the strategic generating unit i at time t
α_{tib}^{S}	Bid price of the strategic generating unit i at time t
α_{tv}^{bidG}	Bid price of virtual generation v at time t
α_{tv}^{bidD}	Bid price of virtual demand v at time t
V_{tv}^{bidG}	Bid quantity of virtual generation v at time t
V_{tv}^{bidD}	Bid quantity of virtual demand v at time t
V_{tv}^{DAg}	Cleared quantity of virtual generation v at time t
V_{tv}^{DAd}	Cleared quantity of virtual demand v at time t
P_{tjb}^{G}	Cleared power generation of unit j of other generators at time t
P_{tdk}^{D}	Cleared power for load d at time t
Ug_{ti}, Ud_{ti}	Binary variables determine the virtual generation or virtual demand
Θ	Objective function value of the second stage problem
MCP_m	FTR auction price for FTR in path m
τ	Lagrangian coefficients of the FTR quantity limitations in the LL problem of the 1st stage optimization model
ξ	Lagrangian coefficients of the line capacity constraints in the LL problem of the 1st stage optimization model
LMP_{tn}	Locational Marginal Price at time t and bus n in the DA market

μ	Lagrangian coefficients of the generation and demand limitation in the LL problem of the 2nd stage optimization model
ϑ	Lagrangian coefficients of the line capacity constraints in the LL problem of the 2nd stage optimization model
γ, u, ω	Binary variables needed to linearize the complementary constraints

1. INTRODUCTION

1.1. DEREGULATION IN POWER INDUSTRY

Power deregulation is the restructuring of the existing power market and seeks to prevent energy monopolies by increasing competition. This growing movement allows power users to choose from multiple power providers based on rates that suit their needs and specialized product offerings.

1.1.1. Background. Nowadays, electricity, as one of the most desirable forms of energy, has become a vital element in human life, and to provide it, large and complicated power systems have appeared in different countries. From the beginning, the management and control of these systems has been the responsibility of the government or quasi-governmental organizations such as municipalities, and although their ownership has rarely been under the authority of the private parties, its management and control structure has been vertical and integrated. In this structure, the production, transmission and distribution of electric energy can be done exclusively by one entity, and it is considered a monopolistic structure. Most of the theories presented in the past about the power system are based on the idea that the electricity sector is a public service sector with exclusive characteristics.

In monopoly markets, local electricity companies have monopoly rights in certain geographical areas. Based on this exclusive right, the electricity company usually has the monopoly of wholesale or even retail sales of electric energy in its territory. Although the external form of this monopoly is different location by location, but it generally means all the privileges as well as all the restrictions of exclusive public services are granted to the electricity companies. In these conditions, the power company is usually committed to provide electric energy to individual consumers at a certain level of reliability and at a fully controlled price [1]. Privatization experiences in industries such as transportation and telecommunications gradually raised the idea of “deregulation” of the power industry [2]. In many countries, the difficulties caused by the inability of the governments to provide the investment and operation costs, pushed the power industry towards privatization. On the other hand, in developed countries, the process of deregulation was a natural consequence of excess energy supply following significant and costly investments in this industry [3]. Moreover, the development of technology, particularly in the generation sector and the improvement of the power plants' efficiencies have facilitated this process, and the growth of international trade, followed by the requirement of the best possible use of primary resources [3], has also strengthened this process.

Chile, as the first country that has experienced deregulation, created competition in the generation sector of the power industry in 1982 due to many difficulties in the management of the power grid and power plants. Then, in 1992, Argentina's power industry, which had previously been viewed as an inefficient industry, was split into three sectors: generation, transmission and distribution, and a competitive market developed in its generation sector. Other South and Central American countries, including Bolivia, Peru, Colombia, Guatemala, El Salvador, Panama, and, to a limited extent, Brazil and Mexico, also experienced similar events [4]. England started this process in Europe, and Scotland and Northern Ireland followed Wales' and England's lead. The market established in Norway in the Scandinavian region gradually expanded to include Sweden, Denmark, and Finland, resulting in the formation of the Nord Pool, one of the most significant active markets worldwide. Spain in 1998 and the Netherlands in 1999 created a competitive market in the generation sector, and this trend is now spreading to Eastern European countries such as Poland, Romania, etc. In New Zealand, Australia and some Canadian states (Alberta and Ontario), deregulation in the electricity industry was proposed as an approach to increase efficiency and reduce costs, and it was gradually implemented. The United States also enacted privatization laws in many states, and ultimately, the states of California, Pennsylvania, New Jersey, and Maryland were acknowledged as the pioneers of deregulation even though the crisis of 2000 and 2001 in California reduced the speed of deregulation process [5].

1.1.2. Economic Motivations for Deregulation. According to economic theories, in order to maximize social welfare and public satisfaction, the price of a commodity must be equal to the marginal cost of its production [6]. Of course, the practical implementation of this proven economic principle is not so simple. There are two approaches that can be utilized to reach this result:

- Creating a regulated structure and forming controlled producers to sell the commodities at a price equal to/close to the marginal cost.
- Relying on the premise that the producers will choose the same price. In other words, creating a natural process for choosing the same price by the producer.

The current structure of the power industry is based on the first assumption. For this reason, only one producer is considered for this product in the traditional structure. It is obvious that if this monopoly producer sets the price of her/his product equal to the marginal cost of its production, she/he cannot obtain the maximum profit. Therefore, in order to prevent the monopoly producer from dominating the market, there is a regulatory entity that oversees this scenario and ensures that prices do not exceed the socially acceptable limits. However, this structure does not have proper efficiency due to the guaranteed profit for the producer since the concept of free selection, which is crucial in many countries, is not included in it, and in addition, the bargaining power of influential groups on the regulator of the market in order to achieve more profit has harmful effects in many countries. Therefore, the monopoly nature of the power industry was questioned, and the prospect of reaching a price equal to the marginal costs of production in a natural way and in a completely free market was considered a strong motivation for deregulation. It is obvious that with this method, in addition to the regulator elimination (along with all its costs), it would be possible to achieve the desired result. Hence, the final purpose of the liberalization of electricity markets was the economic incentive of having a natural way to reach a price at the range of marginal costs and of course improving the efficiency (that is, maximizing social welfare) [7].

In conclusion, attaining two fundamental objectives, namely pricing based on marginal costs and decreasing production costs, may be determined to be the economic incentives for creating competition. Accepting this economic theory leaves little choice but to remove the power industry's monopoly structure, as doing so would require using social resources to cover the expenses of a monopoly system under regulations.

1.1.3. Technical Motivations for Deregulation. The development of power generation and information processing, along with the presence of large and interconnected transmission networks, provided the basis for the implementation of deregulation.

- Small-sized efficient power plants: In the power industry, the most important feature of the monopoly structure from the technological point of view is the reduction of production costs by increasing the size of the power plants. In this way, from an economic point of view, large power plants have advantages over small power plants, which has clearly shown itself in the electricity industry. By enlarging the scale of the power plants from the start of the previous century to almost the end of the 1970s, the investment costs of power plants (per megawatt) as well as their operating costs gradually declined. However, this process was interrupted in the 1980s with the introduction of small and effective combined cycle gas power plants. However, this process was interrupted in the 1980s with the introduction of small and effective combined cycle gas power plants. During those years, it took at least 1000 MW of power plant capacity to lower the fixed average cost (per MWh) and make it competitive, but now, this limit can be met with just a 100 MW combined cycle gas power plant [8]. This trend allowed small producers and/or large industrial consumers to enter the generation market much more easily. In these conditions, it seemed difficult to maintain the monopoly industry's cost advantages, and the prospect of the presence of a large number of players who produce electricity at low costs seemed to be enough to justify market competition and deregulation.
- High Voltage Transmission Line: Existence of transmission infrastructure is another technical justification for deregulation since it makes the transfer of electric power as feasible as possible with the growth of effective transmission networks. For instance, the +400 kV connections between Norway and Germany

provide the technical possibility of electricity transmission between these two countries and in itself is considered an important element in the possible competition between the producers of different countries.

- Information Technology Improvement: New electrical energy transactions were made possible by the development of information technology, the possibility of real-time information, and the increase in computational capacity of computers. These developments also laid the foundation for market financial transactions. Before, it was impossible to conduct these financial and short-term exchanges since they required the rapid processing of a large amount of data.

1.1.4. Shortcomings in Deregulation. The motivations and ideas justifying deregulation have been explained. However, each of these ideas has limitations and shortcomings, some of which have been mentioned in this section.

- Market Power: a factor that can reduce competition and prevent prices from being set based on marginal production costs.
- Marginal cost Increase: Power plants with lower investment costs usually have higher operating marginal costs. If the investment is limited to these power plants, then the price of electricity will increase.
- Reliability Issues: with deregulation, none of the other players consider themselves responsible for the reliability of the system. Therefore, it becomes more difficult to create the reliable system. Reduced reliability standards will likely be taken into consideration more in markets where competition is intense since market participants' primary objective is to increase their own profits.

- Increase in the local price of electricity: With deregulation, electricity in small and remote areas, which was cheap before, will become more expensive.
- Environmental Issue: Although free investment in energy generation may be economically advantageous, it is also vital to assess environmental circumstances to make sure that new power plants aren't harming the environment.
- National energy policies: With the increase of international links in power systems, it becomes difficult to maintain the stability of energy policies at the national level.

1.2. ELECTRICITY MARKETS

Various approached have been presented for the grouping of electricity markets, however, the basis of all these categorizations has been one of the three important factors of competition, types of transactions, or time. In other words, electricity markets can be divided into different groups depending on the level of existing competition, the structure of transactions and the time of their activity. In this section, these categories are briefly discussed.

1.2.1. Competition. Restructuring and deregulation in the power industry has led to the emergence of markets with different competitiveness. If the criterion for grouping markets is the level of competitiveness in them, then they can be divided into four categories [9].

A) Monopoly at all levels: monopoly electricity markets are markets in which the generation, transmission and sale of energy is monopolized by a private company, government organization, or government-affiliated organizations. In these markets, which dominated the power industry before deregulation, there is a possibility of centralized policy making, network control and cost reduction, and the main objective is usually something other than economic profit. In other words, in these conditions, political and social objectives such as improving people's living standards, providing better production conditions, and etc. are usually defined as the ultimate goal of the industry.

B) Competition in production: In this type of market, power plants and generating companies (GenCos) are privately active in the market and compete with each other to sell energy safely and cheaply to a large buyer/consumer. In this type of market, this large buyer entity is responsible of transmission and distribution of energy and there is no possibility of competition in the consumption sector. In these markets, transactions are usually based on bilateral contracts and as a result, the necessary funds for the development of the system are provided. However, consumers bear the risk associated with the market and technology, and there are essentially no incentives to improve power plant performance throughout the course of the contract (Figure 1.1).

C) Competition in the wholesale market: In this model, a wholesale market for energy is formed in which wholesale buyers and sellers of electricity compete with each other for its quantity and price. Large energy buyers have the option of directly choosing their electricity supplier and can directly choose the energy provider they need from among large energy suppliers, although this freedom is not available for small consumers.

D) Retail competition: In this model, which is considered the most complete market in terms of competition, all customers, both small and large, can directly choose the supplier of the energy they need. In such a structure, freedom of choice is available for all consumers and the possibility of competition for the production of cheaper and/or higher quality commodities is available for all producers. In this type of markets, intermediary institutions or brokers also appear, which make it possible to exchange energy between small consumers and producers.

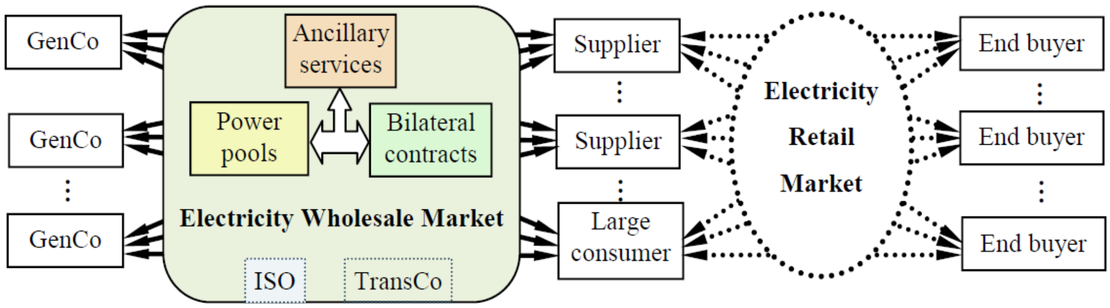


Figure 1.1 The genera market structure of deregulated electricity markets [10].

1.2.2. Transaction types. If the electricity markets are grouped based on the type of energy transactions in them, then three different types of markets can be distinguished in the world. These three types are:

A) Pool-based Markets: There is only one buyer in these markets. “Pool” is actually a governmental or semi-governmental organization that, by receiving price proposals from sellers and starting with the lowest offers, sells the required power to all buyers, usually at a single price, until the demand is fully satisfied. This uniform price is the offer price of the most expensive seller whose power is needed by the buyers. The economic logic of this method is to allocate more profit to more efficient producers [11].

B) Bilateral Contract: In these markets, buyers and sellers negotiate with each other individually and agree on the price. It is possible that all or some of the specifications of these bilateral or multilateral contracts will be provided to the management system. In these systems, the power transfer fee is calculated separately and provided by the producers and/or consumers with the mechanisms foreseen in the bilateral or multilateral contracts.

C) Power Exchange: In this method, a commercial entity is created to manage the market by the government or market participants (MPs), which works exactly like a stock market. Buyers bids their power requirements and sellers offer their generations to the market. Sellers (GenCos) and buyers (Consumers) have really entered the market during commercial exchange and are no longer considered individual sellers or buyers. Just like the stock exchange in the stock market, the power exchange constantly calculates the daily price of a power and provides it to all MPs, which is actually the price of all the power exchanges that take place at that moment [12].

Although there is no contradiction among these three types of markets, simultaneous use of two mechanisms is more common in existing markets. For instance, in some markets, in addition to the presence of the power exchange, bilateral contracts are also allowed. In some other markets, bilateral contracts between large producers and large consumers have been allowed, however, the pool structure has been employed for small companies. The key features of these markets are listed in Table (1.1).

Table 1.1 Key features of various transaction structures in electricity markets.

Transaction Type	No. of buyers	Buyer knows seller?	Uniform Price
Pool	1	Yes	Usually
Bilateral	many	Yes	No
Power Exchange	many	No	Yes

1.2.3. Time Frames of Different Transactions. Based on the transaction period, the existing electricity markets can be divided into three types [13]:

A) Real time market: a market for buying and selling energy in real time. Real-time (RT) electricity market can be managed either privately or by governmental/ government-affiliated organizations and is normally held 5 minutes to 1 hour prior to the operating hours. These markets allow energy generators with additional production to quickly find buyers of this additional energy and agree with them on the price in a few milliseconds, and finally exchange the energy within a few minutes. It is possible for both buyers and sellers to negotiate and offer the price in this market. Due to the fact that its information is made public almost at the same time as energy transactions, this market is particularly tempting to risk-taking MPs.

B) Day-ahead market: The energy market for the next 24 hours is called the day-ahead (DA) market. In this market, which has a greater share of energy transactions in existing restructured systems, producers (and customers) present their offers (bids) for a next 24 hours. Then these offers/bids are evaluated according to the market structure and a balance is created between supply and demand for the next day (Market Clearing Process). After this process, the generation amounts (MW) of each generator as well as the consumption of each consumer along with the hourly energy price for the next day (that is, 24 hours after the start of the market) are fully determined and to informed to both sides.

C) Future energy markets: It is a market for energy in which energies that have not yet been produced are bought and sold. Depending on the types of the markets, the trading methods can be based on auctions and/or based on stock market methods and/or in the form of bilateral contracts. Moreover, the trading period can change from one week to ten years or even more. Trading in this market is dangerous for both the seller and the buyer, because the price of energy at the moment of trading can be completely different (much more or less) than its price at the time of delivery. The sellers can raise their capital wealth by selling their capacity in exchange for this risk, and the buyers can supply the energy they require at prices that are protected from unexpected price increases (Price spikes).

1.3. ELECTRICITY PRICING

How to price commodity and services within a market is unquestionably one of the most crucial foundations of the industry. Power is the output of the electricity market, and the transmission and distribution of this energy are the services offered in this environment. In this section, the pricing methods for energy and transmission services in different markets have been briefly highlighted.

1.3.1. Auction-based Pricing. Energy auctions are the basis for pricing in many electricity markets. This method of pricing ignores the network situation at the time of the auction, and its effects, i.e., the limited transmission line capacities and the power losses, are added to the energy prices in the next stage. This is usually done in two stages and the transmission limit and losses are calculated separately.

1.3.1.1. Energy auction. The purpose of designing an energy market and determining electricity prices is to optimize the general satisfaction of both generators and consumers. For this purpose, an optimization process is typically implemented, the objective function of which is the total surplus of the customer and the generators [14].

The customer's surplus is equal to the multiplication of the accepted consumption bids and its bid price, and the seller's surplus is the multiplication of the cleared generation and its offer price. The main constraint of this optimization is the supply-demand balance constraint at the market settlement point. Additionally, other technical constraints such as maximum and minimum allowed production values should also be considered in this optimization problem. The output of this optimization problem is the amount of generation of all generators and the amount of consumption of all loads, along with their corresponding price. After optimization, the amount of bill and payment of the MPs can be done based on one of the following two approaches:

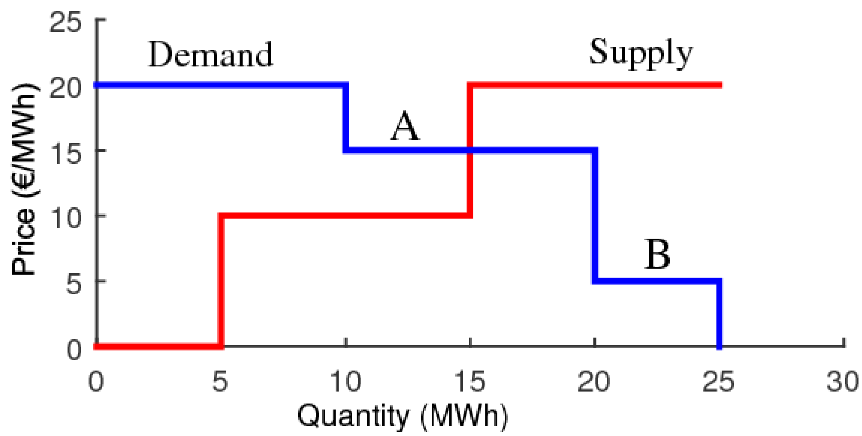


Figure 1.2 Supply and Demand Curves

A) Uniform Pricing [15]: The most widely used method in electricity markets in the world is holding single-price energy auctions in all developed markets (RT, DA markets, etc.). In this method, which is shown in Figure 1.2, after all the generators (and depending on the structure of the market, the consumers) have announced the price and quantity of their offers/bids to the market, the market operator, starting from the lowest offers, forms the supply and demand curves and the intersection point of two curves determine the market price (Market Clearing price (MCP)). In other words, the final price of energy in this type of auction is equal to the offer price of the most expensive generation that is required to meet the market demand. The most important advantage of this method is its economic efficiency. That is, with this method, the most profit is given to the producers who gave the lowest price offer. In addition, it is easy to manage transactions in this method. On the other hand, the most important shortcoming of this method is the possibility of market power formation and the vulnerability of prices from the offers of large producers present in the market.

B) Pay As Bid Pricing [16]: Pricing with this method has been considered as one of the ways to overcome the market power. The principles of this method are the same as the previous method. The only difference between these two methods is the amount of bills and payments of producers and consumers. After clearing the market and determining the cleared powers and the final market price, the price received by the producers will not be the same as the price announces to consumers. In this method, each producer/consumer is paid/pays a price exactly equal to his offer/bid price. The key challenge in this method is linking it with markets where there are lots of producers and customers.

1.3.1.2. Congestion management. The aforementioned methods for determining the production prices and cleared powers ignored the transmission line capacities. In order to manage transmission network congestion, it is typically tried to reduce the overall costs of altering generator output or consumer load (caused by congestion in the network) [17]. In this minimization problem, the transmission line constraints as well as the power balance in all network buses are modeled, and the output of this optimization problem, in addition to the costs of reducing and/or increasing load and production, is the amount of change in consumption or production for all loads and generators connected to the network. There are several other approaches reported in the literature [18, 19] that is not the focus of this work.

1.3.2. Pricing Based on Optimal Power Flow. In this method, after clearing the market and determining the market winners for a specific hour, an optimal power flow (OPF) is carried out, the purpose of which is to minimize the production cost (offer price) of the producers [20]. In the OPF, the loads are assumed to be fixed and the sellers' offer prices are usually modeled as cost curves that increase uniformly with the increase in production level. The constraints of this minimization problem are the equality constraints of active and reactive power in all system buses (in AC power flow), transmission line constraints, bus voltage constraints, and generation capacity constraints. The output of this optimization is the generators' productions along with the locational Marginal Prices (LMPs) in all the busses of the system, in which the congestion and losses costs are included [21].

One benefit of this pricing system over auction-based pricing is the non-separation of congestion costs from energy costs and their simultaneous calculation. However, due to the local nature of LMPs, in this method, a merchandizing surplus appears, which does not exist in the auction-based pricing approach. In other words, in the auction-based method, no direct payment is made to the provider of transmission facilities. Rather, transmission costs are provided through fixed payments, but in Locational Marginal Pricing approach, during periods of congestion, an important part of customer payments is directly provided to transmission companies through the merchandizing surplus.

1.4. MARKET PARTICIPANTS

The transformation of the electricity industry and the change of its vertically integrated structure to a competitive structure has caused the creation of new organizations that are related and appropriate to this new structure. From a general point of view, these organizations can be categorized into two important groups: regulatory-management entities and market participants (MPs).

The regulatory entity has two main activities. Some of these management organizations in electricity markets are responsible for legislation and monitoring the proper functioning of the market, guaranteeing the legal, political and social health of the market. However, another group of these entities are technically in charge of power system management. Independent System Operator (ISO) is the most well-known and important management entity whose proper operation has a substantial impact on the operation of other institutions. The ISO is actually in charge of controlling the network; it determines the transmission tariffs, maintains the security of the system, plans the repair and periodically maintenance, and cooperates in long-term decisions. The operation of ISOs should be independent from the MPs such as transmission system owners, generating companies, distribution companies and end users in order to provide fair access to the transmission system for all users.

There are some other commercial entities who can participate in the electricity markets. In this subsection, some of these MPs are briefly described [22]:

A) Generating Company (GenCo): Generating companies are in charge of operating and maintaining the generating units. These companies can own the power plants or merely operate the production units. The relationship between GenCos and customers is established through short-term markets and long-term energy or power contracts. In addition to active power, GenCos can provide reactive power and reserve, and their function is independent from other market entities such as ISO and transmission companies. A GenCo can either sell its energy through bilateral or multilateral contracts or supply it to large customers through the market. In the competitive electricity market, the main and first objective of every GenCo is to achieve maximum profit. Therefore, to GenCos, “profitability” is the main factor to consider when making long-term or short-term plans to enter certain markets. It goes without saying that in this situation, the company itself would be immediately impacted by the risks associated with these types of decisions.

B) Transmission Company (TransCo): The responsibility of a transmission company is to transfer power from GenCos to distribution companies to satisfy the high voltage demands. ISO controls the transmission facilities although its ownership remains with their original owners. Ownership, maintenance and operation of the transmission system in any specific geographical area is the responsibility of a transmission company. These companies should not be dependent on any of the other institutions of the market so that they can provide a fair path for all power transactions by creating the possibility of free access.to these facilities. The regulations governing the operation of these companies are dictated by governmental entities, and their expenses are provided by consumers by adding these costs to the bills.

C) Distribution Companies (DisCo): Distribution companies use their equipment and facilities to distribute electricity in a specific geographical area. A DisCo is responsible for creating, maintaining, operating and preserving the reliability of the distribution networks as a link between the power end users and the transmission system. This company is also in charge of distribution network shutdowns and maintaining the quality of transmitted power. Moreover, maintaining the voltage level, periodical maintenance and other ancillary services are part of the duties of a distribution company.

D) Retailer: These companies are a relatively new element in the power industry, which are active in retail sales by obtaining a legal license. A retailer buys electric power as well as other services necessary to meet its customers' requirement, then combines them in different ways and offers them for sale.

E) Aggregator: A real or legal person who combines customers as a group of buyers/sellers and thus enters the market as a relatively large buyer/seller. The aggregator can be like a broker or a mediator between customers and retailers.

F) Customers: Customer is the end user of electricity, which is connected to the transmission system (large customer) or the distribution system (small customer). In the vertical integrated structure, the consumer inevitably buys energy from the company that has the monopoly in the region, at the price he determines. However, in deregulated environment, the customer does not have to buy services from local companies but can directly transact with producers or other power providers to buy the electricity or services he needs.

1.4.1. Types of Market Participants in this Work. In this work, MPs are categorized into two main groups: Physical MPs, and Virtual Bidders.

1.4.1.1. Physical market participants. All MPs who own generating units are grouped in this category. These generating units can be a conventional fossil-based generators or renewable generators such as wind, solar, and etc. In this work, it is assumed that the physical MPs owns different kinds of generating units such as coal-based generating units, oil-based generating units, and nuclear-based generating units. Therefore, some physical constraints need to be considered in modeling these MPs based on their types such as ramp up, ramp down, min up time, min down time, and etc.

1.4.1.2. Virtual bidders. virtual market participants or virtual bidders who play in the electricity markets without any assets. They are purely financial players who offer or bid in the DA market without the obligation of providing/consuming the physical energy in the RT market. The net energy in DA market and RT market are zero, while the net profit is calculated in the two-settlement process based on the difference between the DA and RT market prices. These transactions could be either generation that is called increment offer (INC) or demand that is called decrement bid (DEC). In terms of modelling, this player's important feature is the virtual proxy. Virtual proxy is the financial insurance that the virtual bidder needs to deposit in the ISO account to guarantee the ability to pay for the potential loss [23].

1.5. BIDDING STRATEGY

The two primary parties involved in most of the competitive electricity market are the supplier and the customer. In this environment, all power producers and power demands are required to submit offers or bids for the sale and purchase of energy. Bidding strategy is a decision-making process that MPs need to consider submitting their best offer or bids into the market. Many research works have been done on the strategic bidding problem for a competitive power producer, and several modeling techniques have been reported to design the strategic bidding strategies. In general, [10] classified the strategic bidding models into four main categories: (1) Single GenCo optimization Model, (2) Game theory-based models, (3) Agent-based models, and (4) hybrid or other models. In this work, the first modeling approach has been considered and the strategic bidding strategy problem from single GenCo or virtual bidder viewpoints have been studied. More details about the different modeling methods are provided in the literature review section (Section 2).

1.6. MOTIVATION OF THIS WORK

Restructuring involves a variety of activities, including reorganizing current corporations such as GenCos, privatization, and decoupling. The term "wholesale market" refers to the market that exists between GenCos and retailers, large consumers, DisCos, or aggregators. This market can be categorized into two main groups: perfect competition, imperfect competition. The spot electricity market (like DA and RT markets) performs more like an imperfect competitive market due to the small number of generators, the lengthy construction period for power plants, the significant capital expenditure, the transmission constraints, and transmission losses. In this situation, GenCos may offer at higher prices than their marginal costs to increase their profits (strategic bidding problem) [24]. Therefore, GenCos can maximize their payoffs while reducing the corresponding risks by employing the most effective bidding technique in the competitive power spot market. Hence, one of the motivations of this work is to design the effective bidding strategy for strategic MPs in different electricity markets.

Efficient power DA markets typically incorporate virtual bids. These financial contracts are awarded at the DA prices and settled at the RT prices. These virtual bids in PJM take the form of things like increment offers (INCs), which are analogous to generation offers, decrement bids (DECs), which are analogous to demand bids, and up-to-congestion bids (UTCs), which are analogous to transmission price spread bids [25]. These transactions are able to enhance the power market efficiency, reduce market power, improve price formation, and hedge RT market risks. The PJM report generally elaborated the benefits of the virtual bidding from the ISO perspective. However, there are new types of MPs who want to participate in different electricity markets without any assets and maximize their profit. The bidding strategy problem of these kinds of MPs are overlooked in the literature. It is worth mentioning that when making decisions, virtual bidders, like traditional MPs, must consider a variety of uncertainties, including those related to the RT price, rivals' offers/bids, and loads. Therefore, designing the robust bidding strategy for these types of players is another motivation of this work.

Besides the virtual bidders, physical MPs can also take part in virtual bidding in electricity markets. However, their strategy may be totally different from purely financial players because their decisions are totally dependent to the essence of their physical assets. As a result, the decision-making of physical MP with virtual bidding capabilities is a novel and difficult issue that requires more investigation. A physical MP with virtual bidding capability must consider that its objective is to maximize the total profit including the physical generation profit and virtual bid’s profit. Moreover, this player should be aware that the increment offer/decrement bid may alter DA market prices, which may change the profit from the physical generation. It also needs to consider the effect of its physical generation on the DA market price which subsequently alters DA and RT price spread, resulting in changes in the virtual bid's revenue. Therefore, designing the bidding strategy for the physical MP with virtual bidding capability in DA and RT markets while taking into account various uncertain parameters is another driving force behind this study.

Transmission congestion causes a price separation among different buses in the power system in the DA market. Therefore, the payment to the suppliers (such as GenCos) is different from the payment collected from demands. The difference between these payments is called congestion charges or congestion surplus. As a non-beneficiary independent organization, ISO is required to give this surplus to MPs. To do so, it holds a different auction called the Financial Transmission Right (FTR) auction. The value of FTR is obtained by the DA price difference between "sink" and "source" buses, which implies that these two markets are interrelated. Moreover, virtual bid can be employed by strategic MP as a tool to manipulate the DA market price and make the most of these situations. In other words, an MP may leverage this impact from virtual bids to boost its FTR value and enhance its overall strategy for taking part in both the FTR auction and the DA market. In other words, an MP may leverage this impact from virtual bids to boost its FTR value and enhance its overall strategy for taking part in both the FTR auction and the DA market. Thus, another reason for doing this work is to propose a framework for offering strategy for a strategic GenCo that participates in both the FTR auction and the DA market while taking virtual bidding into account.

The literature review about the topic of bidding strategy is briefly described in Section 2. The bidding strategy for the virtual bidder using robust optimization is described in Section 3. Section 4 elaborates on the optimal bidding strategy for a physical MP with virtual bidding capability. In Section 5, the optimal offering strategy for GenCo with joint participation in the FTR auction and the DA Market taking into account virtual bidding is completely outlined, and the dissertation is concluded in Section 6.

1.7. CONTRIBUTIONS OF THIS WORK

The problem of designing bidding strategy for different market participants in various electricity markets is considered in this work. The work exclusively relies on a few general assumptions.

- DC power flow (DCPF) is used to model the transmission network in order to make it consistent with contemporary market practices. The line flows have been computed using the Power Transfer Distribution Factor (PTDF).
- In order to be consistent with the existing approaches used in the energy market, rivals' offers/bids have been modeled using stepwise curves. It is worth noting that these unknown parameters can be calculated and anticipated using public market data that becomes available a few months after market clearing.
- The physical MP provides asset-based physical generation from the buses where the generators are connected. However, it may submit its virtual bids from other locations.

- Similar to the assumption taken in [26, 27], Because of its nonconvexity and inability to track the problem, Unit Commitment (UC) is not taken into account in this work.

In light of the explanations in Section 1.6, the contributions of this study can be summarized into the list below.

- Proposes a bi-level optimization model for optimal bidding strategy of virtual bidders, and physical MP with virtual bidding capability in Day-ahead electricity markets. They are the first models presented for these kinds of MPs participating in spot markets.
- Reveals that the physical MPs may have the incentive to exercise the virtual bidding capability in a very different way than purely financial MPs.
- Considers uncertainties associated with other market participants and with RT market prices. It improved the reliability of the model since it considers the probable circumstances in the formulations. Employs stochastic model and robust optimization to develop the model.
- Takes into account financial risks of bidding strategy using conditional value-at-risk (CVaR). It improves the flexibility of the model to work for either risk-taker or risk-averse MPs.
- Develops a two-stage two-level joint offering strategy paradigm for the strategic GenCo participating in both FTR auction and DA market. The proposed model is enhanced by considering the virtual bidding capability for the strategic GenCo. By employing the test system to place virtual bids in the DA market, this work also illustrates the potential for FTR value manipulation.

2. LITERATURE REVIEW

When power systems are reformed, strategic bidding provides market participants with the opportunity to generate better operation profits. Participants on the supply side of the reformed marketplaces have the chance to improve the efficiency of their business operations, which will allow them to reduce their expenses and increase their profits. The goal of the demand side is to reduce the cost of electricity that is acquired from the grid by taking use of the grid's operational flexibility. As a result, throughout the course of the past several years, a number of different techniques have been described for the purpose of constructing optimal bidding strategies for use in competitive power markets. These current strategies can be divided into two basic categories: those designed for players who take prices (price-taker market participant) and those designed for participants who set prices (price-maker market participant). Therefore, this section will briefly review existing works relevant to this research. Moreover, there are two main group of methods developed for the price-maker players: game-based approach, non-game approach. This section also review some of the works in this area.

2.1. BIDDING STRATEGY FOR PRICE-TAKER MARKET PARTICIPANTS

A player whose offers or bids do not influence the result of the market is referred to as a price-taker market participant. To speak more generally, these participants have no intention of purposefully altering the outputs of the market. These are typically small companies and using the day-ahead market price prediction to develop their bidding strategies [28 – 30].

A bidding rule for a price-taker MP that enables them to attain their best self-schedule even when there is uncertainty regarding the price, is presented in [28]. The hourly market-clearing prices are presented together with an accurate probability description of those values. It is applied to the formulation and resolution of a problem involving the self-scheduling of expected maximum profit. The methodology that is provided [29] enables the identification of bidding tactics for a wind power producer that result in a significant reduction in the risk of profit fluctuation for a very little fall in the expected profit. In addition, this article presents a method for quantifying the positive influence that a series of adjustment markets has after the clearing of the day-ahead market. New IGDT-based formulations are reported in [30] for risk-limited self-scheduling of GenCo under unknown future market prices. It is revealed that for a risk-averse GenCo, the robust formulation in [30] ensures a minimal critical profit if future prices fall within a maximized robustness region. Furthermore, for a risk taker player, the reported formulation allows it to benefit from unforeseen price surges and perhaps make a higher profit. To help the electric vehicle aggregators make the most of opportunities in the RT energy and regulation markets, [31] created a stochastic optimization model. Results from experiments in [31] show that the aggregator's bidding approach benefits greatly from taking into account both instructed and uninstructed energy variations. Bidding strategy of single price-taker pumped-storage power plant in the pool-based electricity market is reported in [32]. An unconstrained optimum bidding strategy for a pumped-storage generator has been designed in [33] starting with an expected market clearing price weekly curve. In order to fulfill the limitations within each time segment while taking reservoir capacity limits into consideration in [33], a multistage-looping optimization has been performed. [34] reported a unique multi-objective bidding strategy outline for a wind-thermal-photovoltaic system in which two main goals were laid in the objective function, the first of which deals with profit maximization and the second of which addresses the reduction of thermal unit emissions. An optimum risk-averse bidding approach was developed in [35] for the resource aggregator in the day-ahead power markets using the set of uncertain scenarios. The forecasted regret value for a selection of the worst-case situations, whose combined probability is no greater than a threshold value, was minimized. It is demonstrated that the suggested method in [35] performs better than benchmark strategies at hedging high regret risks and achieves computational efficiency and DA bidding costs that are comparable to the base cases. A robust optimization-based technique for choosing the bidding strategy for a wind farm with co-located energy storage in a power market is reported in [36] which shows that the combination of wind with storage improves the exploitation of the unreliable wind resource and boosts economic performance by engaging in energy arbitrage. It is represented that the robust optimization-based technique outperforms the deterministic approach economically in the worst case scenario of considerable wind power and electricity price forecast inaccuracy [36].

2.2. BIDDING STRATEGY FOR PRICE-MAKER MARKET PARTICIPANTS

Perfect competitions and imperfect competitions are the two categories that can be used to classify market structures when viewed from the standpoint of microeconomics market competition. There are a huge number of producers and customers that compete on a homogenous commodity in perfect competition. The price of the product is determined by the forces of demand and supply, and no company is able to influence the price of the market by changing their market strategies. On the other hand, the presence of imperfect competition creates the possibility for certain market participants to manipulate market pricing in a way that benefits their own individual interests [5, 37]. Energy generating firms, a significant actor in the imperfect electricity market environment, seek to optimize their profit by implementing offer strategies in one or more markets. In recent years, a significant number of researchers have focused their attention on determining the optimal offering strategy for physical generating companies in a single market or multiple markets. In this context, a great number of methodologies, including optimization-based, game theory-based, and agent-based models, have been investigated within the context of the deregulated electricity market [10]. A binary expansion approach for the price-maker market participant's bidding strategy problem in a spot electricity market has been presented in [38]. A procedure for a power producer to obtain strategic offers for the sale of power in a pool-based electricity market is provided in [39]. Instead of being derived from input data, market prices are produced endogenously in this reported methodology. The fact that the offering methods and demand bids of rival producers are unclear is something that is taken into consideration. The reported method has been shown by numerical simulations to have the ability to identify the strategic opportunities that will result in the highest return on investment. In [40], the bi-level optimization approach was presented to derive the optimum offers for the physical generating company so that it could make the most profit possible. An optimization-based scheduling for a building energy management system and bidding strategy of small-scale residential prosumers are formulated as a stochastic bi-level optimization problem in [41] to minimize the energy cost and prosumer's inconveniences in the upper-level and lower-level, respectively. A non-cooperative game theory approach to design the best strategy for market players was reported in [26] which demonstrate that the generating company's bidding strategies and anticipated rewards are significantly impacted by the expected total profits. However, by using the suggested approach, this player can profit more than the case when they bid at their marginal costs. In [42], strategy analysis using agent-based simulation is provided. In [43], the determination of an optimal strategy for a GenCo in three consecutive markets has been explored. In this study, the generating company is regarded as the price-taker market participant in the day-ahead and automatic generation control (AGC) markets and the price-setter player in the balancing market. According to [44], a multi-stage stochastic model was used to create an offering strategy for a generator in the day-ahead and balancing markets, while [45] used a similar technique to create an optimal bidding strategy for a group of prosumers in the energy and reserve markets. [46] optimized the MPs' offering strategies in the financial transmission right (FTR) auction and day-ahead electricity market using a two-tier matrix game model. This approach reflected the iteratively solved FTR game in the top tier and the energy game in the bottom tier. An optimal bidding for a microgrid (MG) incorporated with the flexible ramping product in multiple markets has been presented in [27], which not only increases the MG's revenue, but also improves the dispatch flexibility in the power system.

2.3. BIDDING STRATEGY AND VIRTUAL BIDDING

Virtual transactions, also known as virtual bids or convergence bids, are useful tools that can be utilized to bridge the price disparity that exists between the locational marginal prices of day-ahead and real-time markets. Financial players can exchange virtual bids as increment offers (INC) or decrement bids (DEC) in the day-ahead market without having any intention of producing or consuming actual power in the real-time market, according to the PJM report [25, 47]. The merits and demerits of virtual bids participating in the day-ahead market, were discussed in [48] – [50]. To enhance the DA scheduling of generating units, virtual bids were used as flexible resources in four different two-settlement market clearing models in [50]. A model with three stages of equilibrium was presented in [51] in order to examine the manipulation in three sequential markets while taking into account the demand and congestion uncertainty. In addition, a numerical simulation conducted on a two-bus system demonstrated that the day-ahead price manipulation through the use of virtual bids, which resulted in the exploitation of FTR positions, was achieved when all players in the day-ahead market participated in the Cournot game. To predict the locational marginal price (LMP) difference between the real-time and day-ahead markets, a Mixed Density Network (MDN) was established in [52]. It presented a data-driven algorithmic bidding method for virtual bids in the day-ahead power market. [53] evaluated the strategy of a photovoltaic producer using the virtual bids and stochastic optimization. [54] presents the ideal bidding decision design for a virtual bidder in the day-ahead market taking into account the risk of profit volatility. In addition to all of the benefits and applications discussed above, virtual bids have the potential to boost the value of FTR in an FTR auction since they can be submitted as generations or loads at specific locations [55]. This ability allows virtual bids to improve the value of FTR. This aspect of virtual bid provides the market players with an opportunity to potentially improve the designs of their bidding approach, which is something that has not been researched in previously published publications

2.4. UNCERTAINTY MANAGEMENT

In almost all research carried out about the bidding strategy problem, it is considered that the design of the bidding strategy is subject to a variety of sources of unpredictability, including market prices, demand, competitor strategies, and the output of renewable energy. The unpredictable actions of competing generators and customers were modeled probabilistically in [56], and a Monte Carlo simulation was utilized to identify the ideal offering strategy for the price-maker market participant whose expected profit was then computed using the results of the simulation. To derive the optimal bidding strategy for a strategic generation company, a stochastic bi-level optimization problem has been modeled in [39], which modeled the uncertainties of consumers' bids and rival generators' offers through multiple scenarios. Using the historical hourly demand curves and the generation price quota curves, the paper [57] uses a self-scheduling model to design the bidding strategy of price-maker energy storage and evaluate the potential arbitrage benefits of these resources in the Alberta electricity market. This evaluation is carried out with the help of the historical hourly demand curves (DPGCs and GPDCs). A two-stage stochastic model is presented in [58] with the purpose of capturing the optimal offering decisions of a strategic wind power producer in the day-ahead and balancing markets. Within this model, scenario-based modeling is utilized to model the uncertainties associated with the wind productions, the behaviors of other players, and the market price. This allows the model to capture the optimal offering decisions of a strategic wind power producer. Optimal bid prices and quantities of a generating company are derived in [59] using a self-organizing hierarchical particle swarm optimization. This is a process in which a risk index based on mean-standard deviation ratio (MSR) is optimized, and Monte Carlo simulation is applied in order to mimic the behaviors of other market players in the electricity market. Robust optimization, which is independent of the probability distribution function (PDF) of the parameters and assumes uncertain intervals around the predicted parameters, has become an appropriate choice for studies with a high level of uncertainties and insufficient data for an accurate forecast of probability distribution functions (PDFs). Robust optimization is one of the many current methods for addressing the uncertainties. In recent times, the robust optimization technique has seen widespread application for the design challenges of bidding strategies. In [60], a two-stage robust optimization approach is employed in order to build the offering strategy of a price-taker virtual power plant (VPP) who is comprised of a wind power producer, energy storage, and a number of demands that participate in the day-ahead and real-time power markets. The goal of [61, 62] was to present a multi-stage distributionally robust optimization (DRO) model whose value was confirmed by the various case studies carried out on the modified Swiss system and Nordpool, which are assumed to act as price-makers in the day-ahead market and as deviators in the balancing market. A stochastic adaptive robust optimization technique has been introduced in [63] to solve the uncertainties related to wind power generation and loads and to attain the optimal behavior of a virtual power plant. The ideal bidding strategy for a hybrid power plant that works as a price-maker in the day-ahead market and a price-taker in the balancing market has been derived in [64]. This method allows the hybrid power plant to participate in both markets while take into account the unpredictability of the price quota curve (PQC) employing the robust optimization. In order to create the best possible plug-in electric vehicle (PEV) charging station, [65] used the bi-level robust optimization model, where the lower-level problem simulated the tactical actions of PEV owners. [66] used the fully modeled generation and demand price quota curves to take into account the impact of the energy storage power on market pricing and recorded the optimal bidding curve of a price-maker energy storage facility in the day-ahead market. The optimal behavior of a price-maker microgrid aggregator (MGA) utilizing a robust optimization model to address the uncertainties related to renewable energy was given in [67] that illustrated that the presented approach can boost MGA profits.

2.5. SECTION SUMMARY

This section looked at a number of publications about the bidding strategy techniques used by various market participants in various power markets. The following summarized table (Table 2.1) is aimed to more accurately depict the differences between the work proposed in this dissertation and the literature.

Table 2.1 Literature review.

Ref	Physical MP	Virtual Bidder	Physical MP with virtual bidding capability	Deterministic Model	Stochastic Model	Robust Model	Risk Modeling	DA Market participation	FTR Auction participation	Joint bidding strategy
[37]	✓			✓				✓		
[24], [27], [38 – 41], [56], [68 – 70]	✓			✓	✓			✓		
[58]	✓			✓	✓		✓	✓		
[23], [52]		✓		✓	✓		✓	✓		
[53]	✓	✓			✓		✓	✓		
[71] – [74]	✓				✓		✓		✓	
[60], [63 – 67], [75]	✓					✓				
This Work	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓

3. BIDDING STRATEGY FOR VIRTUAL BIDDERS IN DAY-AHEAD ELECTRICITY MARKETS

3.1. BACKGROUND

Virtual traders, known as virtual bidders, are solely financial MPs in the power market who can place bids or offers in the DA market without having to use or generate the actual power in RT market. In recent years, these transactions which are designed as decrement bids (DECs) or increment offers (INCs), have been considered as part of the electricity market design [47]. In 2010 and 2011, virtual bids made up about 6% of all transactions in the Midwest Independent Transmission System Operator (MISO) [76] and are typically used to decrease the price difference between the DA and RT markets and boost market liquidity. The benefits and drawbacks of virtual bids in energy market have been reported in [49], which noted that in addition to their advantages, virtual bids may raise the possibility of market manipulation.

Besides, strategic bidding enables MPs in the restructured electrical system to enhance their behavior and maximize their total profits. However, numerous sources of uncertainty, including market prices, demand, rivals' strategies affect the MPs' bidding strategies. There are numerous articles in the literature that cover the uncertainty management (Section 2). Among all current approaches, robust optimization, which is independent of the probability distribution function (PDF) of the parameters, seems to be an appropriate option to manage the uncertainties. Since it considers uncertain intervals around the anticipated parameters rather than constructing numerous scenarios, robust optimization is typically a very suitable choice for a situation with significant levels of uncertainty and inadequate data for an accurate PDFs prediction. Therefore, in this section, the max-min two-level optimization model for a price-maker virtual bidder who plays either generation or load in the DA market, is proposed. In the upper-level of the model, the virtual bidder's profit is maximized, and the market-clearing problem is modeled in a lower-level subproblem. The proposed model can be turned into its equivalent linear single-level problem employing the KKT conditions, duality theory, and strong duality theory (SDT).

3.2. ROBUST BIDDING STRATEGY FOR VIRTUAL BIDDER

The detail of modeling and solution procedure is explained in the following sections.

3.2.1. Virtual Bidding Function. Virtual bidders can participate in energy markets (DA market) with no physical assets. If a virtual bidder is cleared by the ISO to buy (or sell) energy in the DA market for certain time periods, in the ISO two-stage settlement it will be automatically considered to sell (or buy) the same amount of energy in the RT market for the same time periods. As discussed in [54], virtual bidders can improve the market's ability to manage the forecast errors by increasing the liquidity of the market.

One straightforward example is given to help clarify the role of the virtual bidder. Assuming that a virtual bidder predicts the RT price to be higher than the predicted DA price, there will be an opportunity for the virtual bidder to arbitrage between the DA and RT markets by buying a certain amount of energy in the DA market at a DA market price and selling the same amount of energy in the RT market at a RT market price. As a result of this virtual bidder participation, the DA market price may increase due to the increased load cleared in the DA market. Consequently, the difference between DA and RT prices may become smaller, as illustrated in Figure 3.1. Therefore, virtual bidder participation in energy markets may reduce the price gap between DA and RT markets, which is considered an improvement in market convergence.

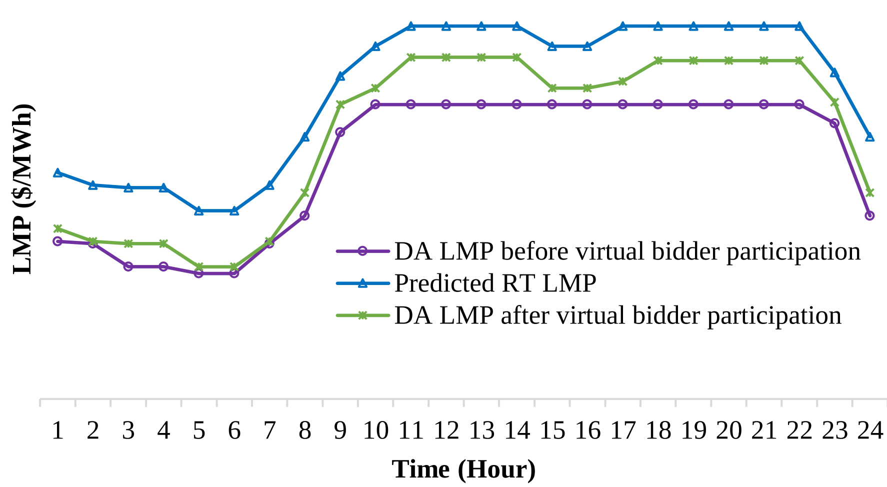


Figure 3.1 The effect of virtual transactions on DA price and DA/RT price difference.

3.2.2. Model Structure. The upper-level subproblem of the proposed two-level approach represents the profit maximization of a virtual bidder, whose decisions (virtual bid quantity and price ($V_{ti}^{bid}, \alpha_{ti}^{bid}$)) are then passed to the lower-level subproblem. The lower-level subproblem represents the quasi market where energy and market prices are cleared on an hourly granularity on a daily basis. The market results (i.e., cleared virtual quantity and market price ($V_{ti}^{DA}, \lambda_{tn}^{DA}$)) are fed back to the upper-level subproblem, which provides a closed loop response of the virtual bidder decision on market price (Figure 3.2). To optimize the virtual bidder's decision, it needs to consider various parameters, including the quantities and prices of other generators'/loads' offers/bids, as well as RT market prices.

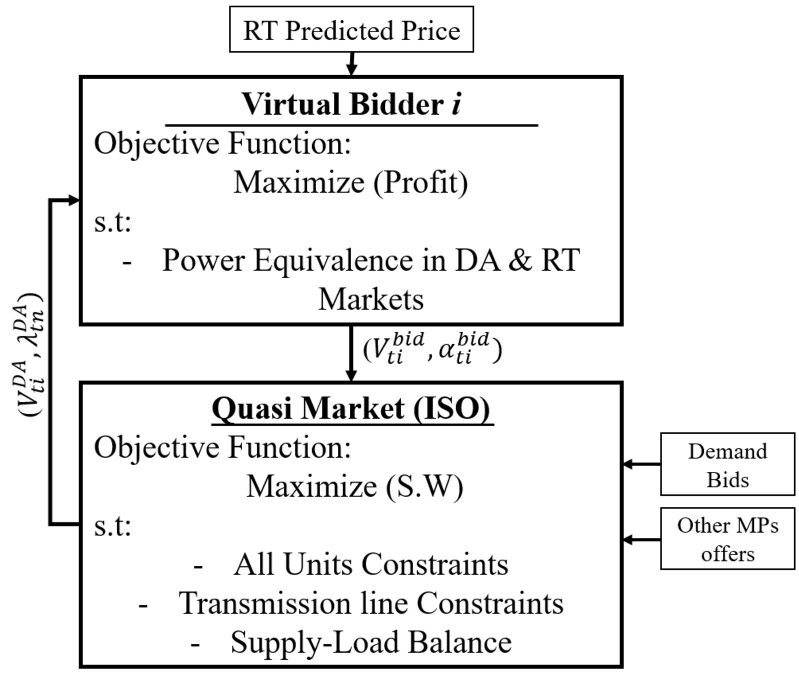


Figure 3.2 Proposed Bi-level Model.

All these parameters play a critical role in the virtual bidder's ultimate profit. For instance, the offers/bids of different competitors may change the DA market price, which is used by the virtual bidder to calculate its DA profit. Furthermore, the RT price helps the virtual bidder to evaluate the DA profit versus the RT profit and deciding whether to be virtual generation or virtual demand in the DA market. As these parameters are unknown to the virtual bidder, they need to be forecasted or estimated. However, making a precise prediction is practically impossible. Therefore, to consider the risks of the forecasted uncertainty sources, a robust optimization approach is employed in this work, which is widely applied by the risk-averse market participants [77]. In this approach, a confidence interval needs to be introduced around an uncertain parameter, then the worst-case scenario of uncertain circumstances within this permissible limit is assessed [66]. Therefore, the proposed max-min two-level optimization model can be formulated as follows.

3.2.3. Proposed Robust Optimization Mathematical Model. The main model for each level of the proposed approach can be formulated as follows.

3.2.3.1. Main model. The upper-level model is the virtual profit maximization model.

A) Upper-Level: Maximize the Profit (Model (1))

$$\underset{\Omega}{\text{Max.}}\ \underset{\Gamma}{\text{Min.}} \sum_{t} \sum_{(i \in \psi_n)} [\lambda_{tn}^{DA} - (\lambda_{tn}^{RT} + \Delta\lambda_{tn}^{RT})]\,(V_{ti}^{DAg} - V_{ti}^{DAd}) \tag{3.1}$$

Subject to:

$$0 \leq V_{ti}^{bidG} \leq V_{ti}^{budget} Ug_{ti}, \quad \forall t, \forall i \tag{3.2}$$

$$0 \leq V_{ti}^{bidD} \leq V_{ti}^{budget} Ud_{ti}, \quad \forall t, \forall i \tag{3.3}$$

$$Ug_{ti} + Ud_{ti} \leq 1, \qquad \forall t, \forall i \tag{3.4}$$

$$\alpha_{ti}^{bidG} \geq 0, \ \ \alpha_{ti}^{bidD} \geq 0, \qquad \forall t, \forall i \tag{3.5}$$

$$-\zeta_n^{RT} \lambda_{tn}^{RT} \leq \Delta\lambda_{tn}^{RT} \leq \zeta_n^{RT} \lambda_{tn}^{RT} \tag{3.6}$$

$$-\sigma_{jb}^{G} \bar{P}_{tjb}^{G} \leq \Delta P_{tjb}^{G} \leq \sigma_{jb}^{G} \bar{P}_{tjb}^{G} \tag{3.7}$$

$$-\sigma_{dk}^{D} \bar{P}_{tdk}^{D} \leq \Delta P_{tdk}^{D} \leq \sigma_{dk}^{D} \bar{P}_{tdk}^{D} \tag{3.8}$$

$$-\tau_{jb}^{G} \lambda_{tjb}^{G} \leq \Delta\lambda_{tjb}^{G} \leq \tau_{jb}^{G} \lambda_{tjb}^{G} \tag{3.9}$$

$$-\tau_{dk}^{D} \lambda_{tdk}^{D} \leq \Delta\lambda_{tdk}^{D} \leq \tau_{dk}^{D} \lambda_{tdk}^{D} \tag{3.10}$$

The lower level represents the hourly-based quasi day-ahead clearing model, which takes the offer quantity and price of the virtual bidder as parameters.

B) Lower-Level: Quasi DA Market (Model (2))

$$\underset{\Xi}{\text{Min.}} \sum_t \left(\sum_i (\alpha_{ti}^{bidG} V_{ti}^{DAg} - \alpha_{ti}^{bidD} V_{ti}^{DAd}) + \sum_j \sum_b (\lambda_{tjb}^G + \Delta\lambda_{tjb}^G) P_{tjb}^G - \sum_d \sum_k (\lambda_{tdk}^D + \Delta\lambda_{tdk}^D) P_{tdk}^D \right) \tag{3.11}$$

$$\Xi = \{V_{ti}^{DAg}, V_{ti}^{DAd}, P_{tjb}^G, P_{tdk}^D\}$$

Subject to:

$$\sum_i (V_{ti}^{DAg} - V_{ti}^{DAd}) + \sum_j \sum_b P_{tjb}^G = \sum_d \sum_k P_{tdk}^D, \quad : \lambda_{tf}^{DA}, \qquad \forall t \tag{3.12}$$

$$0 \le V_{ti}^{DAg} \le V_{ti}^{bidG} \;\; : \; \underline{\mu}_{ti}^{Vg}, \bar{\mu}_{ti}^{Vg}, \quad \forall t, \forall i \tag{3.13}$$

$$0 \le V_{ti}^{DAd} \le V_{ti}^{bidD} \;\; : \underline{\mu}_{ti}^{Vd}, \bar{\mu}_{ti}^{Vd}, \quad \forall t, \forall i \tag{3.14}$$

$$0 \le P_{tjb}^G \le \bar{P}_{tjb}^G + \Delta P_{tjb}^G \;\; : \; \underline{\mu}_{tjb}^G, \bar{\mu}_{tjb}^G, \quad \forall t, \forall j, \forall b \tag{3.15}$$

$$0 \le P_{tdk}^D \le \bar{P}_{tdk}^D + \Delta P_{tdk}^D : \underline{\mu}_{tdk}^D, \bar{\mu}_{tdk}^D, \quad \forall t, \forall d, \forall k \tag{3.16}$$

$$-\bar{C}_l \le \sum_n H_{nl} \left(\sum_{(i \in \psi_n)} (V_{ti}^{DAg} - V_{ti}^{DAd}) + \sum_{(j \in \psi_n)} \sum_b P_{tjb}^G - \sum_{(d \in \psi_n)} \sum_k P_{tdk}^D \right) \le \bar{C}_l \quad : \underline{\vartheta}_{tl}, \overline{\vartheta}_{tl} \;\; \forall t, \forall l \tag{3.17}$$

$$\lambda_{tn}^{DA} = \lambda_{tf}^{DA} - \sum_l H_{nl} (\overline{\vartheta}_{tl} - \underline{\vartheta}_{tl}), \forall t, \forall n \tag{3.18}$$

As it is seen in *Model (1)*, the objective function of the virtual bidder is maximized regarding to its main variables $\Omega = \left\{\alpha_{ti}^{bidG}, V_{ti}^{bidG}, \alpha_{ti}^{bidD}, V_{ti}^{bidD}, Ug_{ti}, Ud_{ti}\right\}$ and minimized with respect to the uncertain parameters $\Gamma = \{\Delta\lambda_{tn}^{RT},\ \Delta P_{tjb}^{G},\ \Delta P_{tdk}^{D},$ $\Delta\lambda_{tjb}^{G}, \Delta\lambda_{tdk}^{D}\}$. Constraints (3.2) and (3.3) set the maximum bounds for the virtual bids (generation/demand). Constraint (3.4) guarantees that virtual generation and demand cannot be submitted to the DA market simultaneously. Uncertain parameters are limited in (3.5) – (3.10) by means of corresponding confidence intervals. The robust parameters ζ_{n}^{RT}, σ_{jb}^{G}, σ_{dk}^{D}, τ_{jb}^{G}, and τ_{dk}^{D} are determined by the virtual bidder and used as known parameters to measure the length of uncertain range around the predicted values. Note that the correlation between uncertain variables can be reflected in the corresponding bounds in this model. Furthermore, the model is flexible to take into account size-varying bounds of uncertain variables for different time periods.

Model (2) represents the lower-level subproblem which is linear since the ISO takes α_{ti}^{bidG} and α_{ti}^{bidD} and V_{ti}^{bidG} and V_{ti}^{bidD} as parameters. Therefore, it can be substituted by its KKT conditions.

3.2.3.2. Equivalent MILP formulations. Combining these equivalenced constraints in the upper-level subproblem results in a Mathematical Problem with Equilibrium Constraint (MPEC), whose formulation is as follows.

A) MPEC Model (Model (3))

$$\underset{\Omega}{\text{Max.}}\ \underset{\Gamma}{\text{Min.}} \sum_{t} \sum_{(i \in \psi_n)} \left(\lambda_{tn}^{DA} - (\lambda_{tn}^{RT} + \Delta\lambda_{tn}^{RT})\right) (V_{ti}^{DAg} - V_{ti}^{DAd}) \tag{3.19}$$

Subject to:

Constraints (3.2) – (3.10) (3.20)

$$\alpha_{ti}^{bidG} - \lambda_{tn}^{DA} + \bar{\mu}_{ti}^{Vg} - \underline{\mu}_{ti}^{Vg} = 0, \qquad \forall t, \forall i \in \psi_n \tag{3.21}$$

$$-\alpha_{ti}^{bidD} + \lambda_{tn}^{DA} + \bar{\mu}_{ti}^{Vd} - \underline{\mu}_{ti}^{Vd} = 0, \qquad \forall t, \forall i \in \psi_n \tag{3.22}$$

$$\lambda_{tjb}^{G} + \Delta\lambda_{tjb}^{G} - \lambda_{tn}^{DA} + \bar{\mu}_{tjb}^{G} - \underline{\mu}_{tjb}^{G} = 0, \qquad \forall t, \forall j \in \psi_n, \forall b \tag{3.23}$$

$$-\lambda_{tdk}^{D} - \Delta\lambda_{tdk}^{D} + \lambda_{tn}^{DA} + \bar{\mu}_{tdk}^{D} - \underline{\mu}_{tdk}^{D} = 0, \;\; \forall t, \forall d \in \psi_n, \forall k \tag{3.24}$$

Constraints (3.12) and (3.18) (3.25)

$$0 \le V_{ti}^{DAg} \perp \underline{\mu}_{ti}^{Vg} \ge 0, \quad \forall t, \forall i \tag{3.26}$$

$$0 \le V_{ti}^{DAd} \perp \underline{\mu}_{ti}^{Vd} \ge 0, \quad \forall t, \forall i \tag{3.27}$$

$$0 \le P_{tjb}^{G} \perp \underline{\mu}_{tjb}^{G} \ge 0, \quad \forall t, \forall j, \forall b \tag{3.28}$$

$$0 \le P_{tdk}^{D} \perp \underline{\mu}_{tdk}^{D} \ge 0, \quad \forall t, \forall d, \forall k \tag{3.29}$$

$$0 \le V_{ti}^{bidG} - V_{ti}^{DAg} \perp \bar{\mu}_{ti}^{Vg} \ge 0, \quad \forall t, \forall i \tag{3.30}$$

$$0 \le V_{ti}^{bidD} - V_{ti}^{DAd} \perp \bar{\mu}_{ti}^{Vd} \ge 0, \quad \forall t, \forall i \tag{3.31}$$

$$0 \le \bar{P}_{tjb}^{G} + \Delta P_{tjb}^{G} - P_{tjb}^{G} \perp \bar{\mu}_{tjb}^{G} \ge 0, \quad \forall t, \forall j, \forall b \tag{3.32}$$

$$0 \le \bar{P}_{tdk}^{D} + \Delta P_{tdk}^{D} - P_{tdk}^{D} \perp \bar{\mu}_{tdk}^{D} \ge 0, \quad \forall t, \forall d, \forall k \tag{3.33}$$

$$0 \le \bar{C}_l + \sum_n H_{nl} \left(\sum_{(i \in \psi_n)} (V_{ti}^{DAg} - V_{ti}^{DAd}) + \sum_{(j \in \psi_n)} \sum_b P_{tjb}^{G} - \sum_{(d \in \psi_n)} \sum_k P_{tdk}^{D} \right) \perp \underline{\vartheta}_{tl} \ge 0, \qquad \forall t, \forall l \tag{3.34}$$

$$0 \le \bar{C}_l - \sum_n H_{nl} \left(\sum_{(i \in \psi_n)} (V_{ti}^{DAg} - V_{ti}^{DAd}) + \sum_{(j \in \psi_n)} \sum_b P_{tjb}^{G} - \sum_{(d \in \psi_n)} \sum_k P_{tdk}^{D} \right) \perp \bar{\vartheta}_{tl} \ge 0, \qquad \forall t, \forall l \tag{3.35}$$

Complementarity constraints related to inequality constraints are stated by (3.26) – (3.35) which are nonlinear equations, which can be linearized using the Fortuny-Amat transformation (Big M method) described in [78 – 79]. Thus, each of the equations of $0 \leq V_{ti} \perp \ d_{ti}(x) \geq 0$ can be rewritten as follows.

$$0 \leq V_{ti} \leq M_{ti}\ \omega_{ti}, \tag{3.36}$$

$$0 \leq \ d_{ti}(x) \leq (1-\omega_{ti})\ M_{ti} \tag{3.37}$$

where M_{ti} is a large number and ω_{ti} is a binary variable. Therefore, the equivalent model will be as *Model (4).*

B) Equivalent MILP Formulation (Model (4))

Objective Function (3.19) (3.38)

Subject to:

Constraints (3.20) – (3.25) (3.39)

Linearized form of (3.26) – (3.35) based on Big M method (3.40)

Now, the only nonlinear equation in *Model (4)* is the objective function, which is expressed explicitly with regard to uncertainties (Γ). To linearize the objective function, at the first step, it needs to be described implicitly based on Γ, which can be done using the SDT [39]. Due to the linearity of the inner problem, SDT can provide an objective function that has a zero duality-gap with the primal objective function value at the optimal point [80]. Doing some mathematical simplification, the objective function (3.38) can be implicitly expressed with respect to the uncertain variables Γ as follows (Equation (3.41)):

Therefore, *Model (4)* represents the single level nonlinear max-min problem. In order to remove the nonlinearities in the objective function, duality theorem is used here.

Since the internal optimization problem (which is with regard to uncertain set) is linear, the dual form of that can be replaced. This procedure is fully illustrated in [81].

$$\underset{\Omega}{\mathrm{Max.}}\,\underset{\Gamma}{\mathrm{Min.}}\sum_{t}\Bigg[\sum_{d}\sum_{k}(\lambda_{tdk}^{D}+\Delta\lambda_{tdk}^{D})P_{tdk}^{D}-\sum_{i}(\lambda_{tn}^{RT}+\Delta\lambda_{tn}^{RT}))(V_{ti}^{DAg}-V_{ti}^{DAd}) \\ -\sum_{j}\sum_{b}\left(\lambda_{tjb}^{G}+\Delta\lambda_{tjb}^{G}\right)P_{tjb}^{G}-\sum_{j}\sum_{b}\bar{\mu}_{tjb}^{G}\left(\bar{P}_{tjb}^{G}+\Delta P_{tjb}^{G}\right) \\ -\sum_{d}\sum_{k}\bar{\mu}_{tdk}^{D}(\bar{P}_{tdk}^{D}+\Delta P_{tdk}^{D})-\sum_{l}\bar{\mathrm{C}}_{l}\left(\overline{\vartheta}_{tl}+\underline{\vartheta}_{tl}\right)\Bigg] \tag{3.41}$$

Employing this approach to *Model (4)* leads us to the following linear maximization form (*Model (5)*).

C) Final Model (Model (5))

$$\underset{\Omega,\Phi}{\mathrm{Max}}\ Z \tag{3.42}$$

$\Phi=\{\bar{\rho}_{tn}^{RT},\underline{\rho}_{tn}^{RT},\bar{\eta}_{tjb}^{G},\underline{\eta}_{tjb}^{G},\bar{\eta}_{tdk}^{D},\underline{\eta}_{tdk}^{D},\bar{\theta}_{tjb}^{G},\underline{\theta}_{tjb}^{G},\bar{\theta}_{tdk}^{D},\underline{\theta}_{tdk}^{D},\bar{\chi}_{tjb}^{G},\underline{\chi}_{tjb}^{G},\bar{\chi}_{tdk}^{D},\underline{\chi}_{tdk}^{D},$ and all dual variables of the lower level

Subject to:

$$\sum_{t}\Bigg[\sum_{d}\sum_{k}\left\{\tau_{dk}^{D}\lambda_{tdk}^{D}\left(\bar{\theta}_{tdk}^{D}-\underline{\theta}_{tdk}^{D}\right)+\sigma_{dk}^{D}\bar{P}_{tdk}^{D}\left(\bar{\eta}_{tdk}^{D}-\underline{\eta}_{tdk}^{D}\right)+\lambda_{tdk}^{D}P_{tdk}^{D} \\ -\bar{\mu}_{tdk}^{D}\bar{P}_{tdk}^{D}\right\} \\ +\sum_{i}\left\{\zeta_{n}^{RT}\lambda_{tn}^{RT}\left(\bar{\rho}_{tn}^{RT}-\underline{\rho}_{tn}^{RT}\right)-\lambda_{tn}^{RT}(V_{ti}^{DAg}-V_{ti}^{DAd})\right\} \\ +\sum_{j}\sum_{b}\left\{\tau_{jb}^{G}\lambda_{tjb}^{G}\left(\bar{\theta}_{tjb}^{G}-\underline{\theta}_{tjb}^{G}\right)+\sigma_{jb}^{G}\bar{P}_{tjb}^{G}\left(\bar{\eta}_{tjb}^{G}-\underline{\eta}_{tjb}^{G}\right) \\ -\lambda_{tjb}^{G}P_{tjb}^{G}-\bar{\mu}_{tjb}^{G}\bar{P}_{tjb}^{G}\right\}-\sum_{l}\bar{\mathrm{C}}_{l}\left(\overline{\vartheta}_{tl}+\underline{\vartheta}_{tl}\right)\Bigg]\geq Z \tag{3.43}$$

Constraints (3.39) and (3.40) (3.44)

$$\bar{\rho}_{tn}^{RT} + \underline{\rho}_{tn}^{RT} = V_{ti}^{DAd} - V_{ti}^{DAg}, \forall t, \forall i \in \psi_n \tag{3.45}$$

$$\sigma_{jb}^{G} \bar{P}_{tjb}^{G} \left(\bar{\chi}_{tjb}^{G} - \underline{\chi}_{tjb}^{G} \right) \geq P_{tjb}^{G} - \bar{P}_{tjb}^{G}, \forall t, \forall j, \forall b \tag{3.46}$$

$$\sigma_{dk}^{D} \bar{P}_{tdk}^{D} \left(\bar{\chi}_{tdk}^{D} - \underline{\chi}_{tdk}^{D} \right) \geq P_{tdk}^{D} - \bar{P}_{tdk}^{D}, \forall t, \forall d, \forall k \tag{3.47}$$

$$\sigma_{jb}^{G} \bar{P}_{tjb}^{G} \left(\bar{\chi}_{tjb}^{G} - \underline{\chi}_{tjb}^{G} \right) \leq \left(1 - \bar{\varpi}_{tjb}^{G}\right) M^{P} + P_{tjb}^{G} - \bar{P}_{tjb}^{G}, \forall t, \forall j, \forall b \tag{3.48}$$

$$\sigma_{dk}^{D} \bar{P}_{tdk}^{D} \left(\bar{\chi}_{tdk}^{D} - \underline{\chi}_{tdk}^{D} \right) \leq (1 - \bar{\varpi}_{tdk}^{D}) M^{P} + P_{tdk}^{D} - \bar{P}_{tdk}^{D}, \forall t, \forall d, \forall k \tag{3.49}$$

$$\tau_{jb}^{G} \lambda_{tjb}^{G} \left(\bar{\pi}_{tjb}^{G} - \underline{\pi}_{tjb}^{G} \right) = \lambda_{tn}^{DA} - \lambda_{tjb}^{G} - \bar{\mu}_{tjb}^{G} + \underline{\mu}_{tjb}^{G}, \quad \forall t, \forall j, \forall b \tag{3.50}$$

$$\tau_{dk}^{D} \lambda_{tdk}^{D} \left(\bar{\pi}_{tdk}^{D} - \underline{\pi}_{tdk}^{D} \right) = -\lambda_{tn}^{DA} + \lambda_{tdk}^{D} - \bar{\mu}_{tdk}^{D} + \underline{\mu}_{tdk}^{D}, \forall t, \forall d, \forall k \tag{3.51}$$

$$\bar{\eta}_{tjb}^{G} + \underline{\eta}_{tjb}^{G} = -\bar{\mu}_{tjb}^{G}, \quad \forall t, \forall j, \forall b \tag{3.52}$$

$$\bar{\eta}_{tdk}^{D} + \underline{\eta}_{tdk}^{D} = -\bar{\mu}_{tdk}^{D}, \quad \forall t, \forall d, \forall k \tag{3.53}$$

$$\bar{\theta}_{tjb}^{G} + \underline{\theta}_{tjb}^{G} = -P_{tjb}^{G}, \forall t, \forall j, \forall b \tag{3.54}$$

$$\bar{\theta}_{tdk}^{D} + \underline{\theta}_{tdk}^{D} = P_{tdk}^{D}, \quad \forall t, \forall d, \forall k \tag{3.55}$$

$$\bar{\chi}_{tjb}^{G} + \underline{\chi}_{tjb}^{G} = -1, \forall t, \forall j, \forall b \tag{3.56}$$

$$\bar{\chi}_{tdk}^{D} + \underline{\chi}_{tdk}^{D} = -1, \forall t, \forall d, \forall k \tag{3.57}$$

$$\bar{\pi}_{tjb}^{G} + \underline{\pi}_{tjb}^{G} = -1, \forall t, \forall j, \forall b \tag{3.58}$$

$$\bar{\pi}_{tdk}^{D} + \underline{\pi}_{tdk}^{D} = -1, \forall t, \forall d, \forall k \tag{3.59}$$

$$\left\{ \bar{\rho}_{tn}^{RT}, \bar{\chi}_{tjb}^{G}, \bar{\chi}_{tdk}^{D}, \bar{\pi}_{tjb}^{G}, \bar{\pi}_{tdk}^{D}, \bar{\eta}_{tjb}^{G}, \bar{\eta}_{tdk}^{D}, \bar{\theta}_{tjb}^{G}, \bar{\theta}_{tdk}^{D} \right\} \leq 0$$
$$\left\{ \underline{\rho}_{tn}^{RT}, \underline{\chi}_{tjb}^{G}, \underline{\chi}_{tdk}^{D}, \underline{\pi}_{tjb}^{G}, \underline{\pi}_{tdk}^{D}, \underline{\eta}_{tjb}^{G}, \underline{\eta}_{tdk}^{D}, \underline{\theta}_{tjb}^{G}, \underline{\theta}_{tdk}^{D} \right\} \geq 0$$

In Model (5), constraints (3.44), (3.46), and (3.52) - (3.55) are the dual forms of the objective function (3.41) with respect to its corresponding constraints (3.5) – (3.10). Lagrangian coefficients of these constraints are $\bar{\rho}_{tn}^{RT}$, $\underline{\rho}_{tn}^{RT}$, $\bar{\eta}_{tjb}^{G}$, $\underline{\eta}_{tjb}^{G}$, $\bar{\eta}_{tdk}^{D}$, $\underline{\eta}_{tdk}^{D}$, $\bar{\theta}_{tjb}^{G}$,

$\underline{\theta}_{tjb}^{G}$, $\bar{\theta}_{tdk}^{D}$, and $\underline{\theta}_{tdk}^{D}$. Constraints (3.46) – (3.51) are the dualized constraints of the primal constraints (3.15), (3.16), (3.32), (3.33), (3.23), and (3.24). Dualized equations of constraints (3.7) – (3.10) are stated as (3.56) – (3.59), respectively. Variables $\bar{\chi}_{tjb}^{G}$, $\underline{\chi}_{tjb}^{G}$, $\bar{\chi}_{tdk}^{D}$, $\underline{\chi}_{tdk}^{D}$, $\bar{\pi}_{tjb}^{G}$, $\underline{\pi}_{tjb}^{G}$, $\bar{\pi}_{tdk}^{D}$, and $\underline{\pi}_{tdk}^{D}$ are the Lagrangian coefficients of (3.6) – (3.10) to evaluate the dual of constraints (3015), (3.16), (3.23), (3.24), (3.32), and (3.33). With this method, which is well described in [81], the robust two-level optimization problem is converted to a single level MILP problem which can be solved by available commercial solvers.

3.3. ILLUSTRATIVE EXAMPLE

The considered test system is illustrated in Figure 3.3. This system includes 5 generators, 3 loads, and 6 transmission lines. It is assumed that the virtual bidder attends to submit its bids from two locations (bus B and bus E) to the DA market.

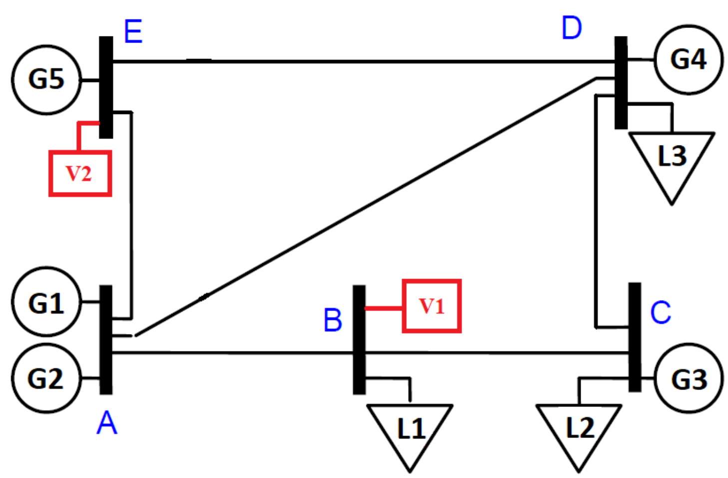


Figure 3.3 Five-bus test system.

For the sake of simplicity, it is assumed that the problem is solved for one period, and the corresponding forecasted RT prices ($/MWH) for different buses are shown in Table 3.1. Forecasted generators'/loads' offers/bids are summarized in Table 3.2 and Table 3.3, respectively.

Line capacities are assumed to be 400MW for the line A-B, 240MW for the line D-E, and 100MW for the rest of the lines. All robustness parameters are 0.1, and V_{ti}^{budget} is 200MW for virtual bids maximum offers/bids. Solving the Deterministic model (Note that this model can be obtained by setting all robustness parameters to zero), the virtual bidder's strategy would be 28.14MW generation at the price of $57.57/MWH at bus B, and 200MW generation at the price of $20/MWH at bus E. As it is shown in Table 3.4, if we test the Deterministic model results in the worst-case scenario, none of these virtual bids are cleared since, in this case, these bid prices are higher than the LMP of the system at the corresponding nodes.

Table 3.1 Forecasted RT Price for Different Buses.

Bus # Hour	**A**	**B**	**C**	**D**	**E**
1	12	50	30	45	10

Table 3.2 Forecasted Generators Offer Quantities and Prices.

	$\overline{P}_{tjb}^{G}$ **(MW)**	λ_{tjb}^{G} **($/MWH)**	**Location (Bus #)**
G_1	40	14	A
G_2	170	15	A
G_3	520	30	C
G_4	200	40	D
G_5	600	20	E

Table 3.3 Forecasted Loads Bid Quantities and Prices.

	$\overline{P}_{tdk}^{D}$ (MW)	λ_{tdk}^{D} ($/MWH)	Location (Bus #)
L_1	300	60	B
L_2	300	60	C
L_3	400	75	D

Table 3.4 Deterministic and Robust Models Results in the Worst-Case Scenario.

		α_{ti}^{bidG} ($/MWH)	α_{ti}^{bidD} ($/MWH)	V_{ti}^{bidG} (MW)	V_{ti}^{bidD} (MW)	V_{ti}^{DAg} (MW)	V_{ti}^{DAd} (MW)
Deterministic	V_1	57.57	0	28.14	0	0	0
	V_2	20	0	200	0	0	0
Robust	V_1	0	66	0	19	0	19
	V_2	18	0	200	0	200	0

On the contrary, the bidding strategy of the virtual bidder is completely different when he/she applies the proposed model (*Model (5)*). As this model considers the occurrence of the worst-case scenario, its solution will be optimal in this scenario. The worst-case scenario happens when the L_1 and G_5 are the marginal MPs at buses B and E, respectively. As the robustness parameters are 0.1, the LMPs will be $66/MWH at bus B and $18/MWH at bus E, in the worst-case scenario. Therefore, virtual bidder bids as a demand at bus B at the price of $66/MWH and as a generator at bus E at the price of $18/MWH to be cleared in the DA market in this situation. As a result, the total profit of the virtual bidder is $404 using the proposed robust model at the worst-case scenario, while the profit would be zero when bids obtained from the Deterministic model are used.

3.4. CASE STUDY

To represent the effectiveness of the model, the following case study is designed.

3.4.1. Data and Case Setups. The proposed approach is implemented on the IEEE 24-bus Reliability Test System [82] (Figure 3.4). This system includes 24 buses, 32 generators, 17 demands, and 38 transmission lines. A virtual bidder is assumed to bid from 5 different locations (buses #6, #11, #14, #16, #22). Suppose the maximum bid quantity that virtual bidder can bid in the DA market is 60MW, which is determined according to the proxy amount owned by the virtual bidder [52].

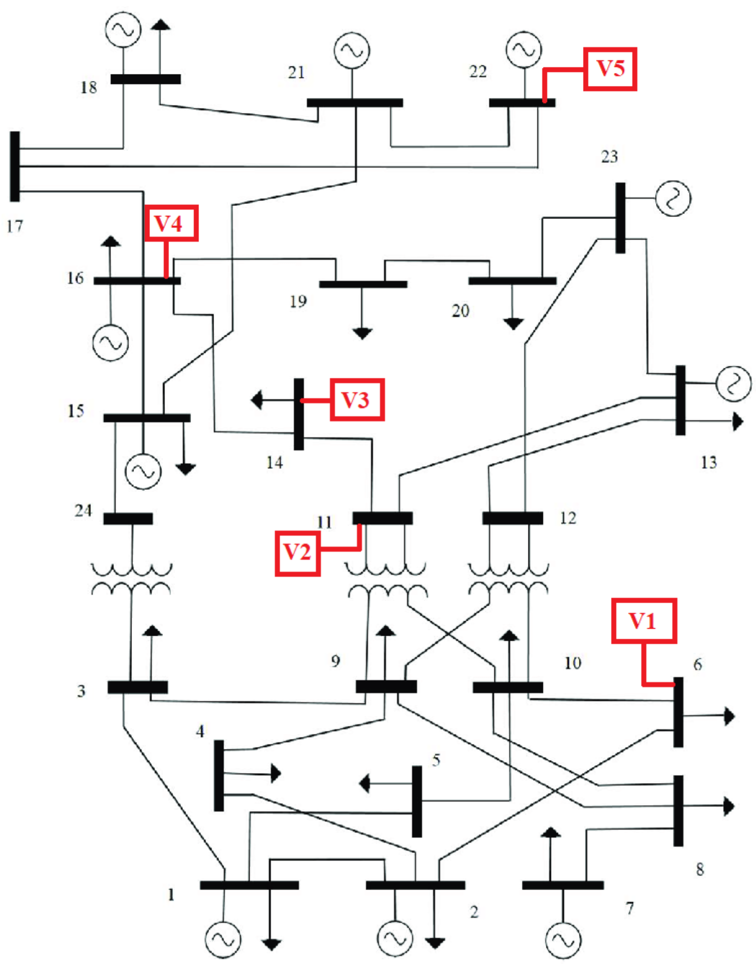


Figure 3.4 IEEE 24-bus test system.

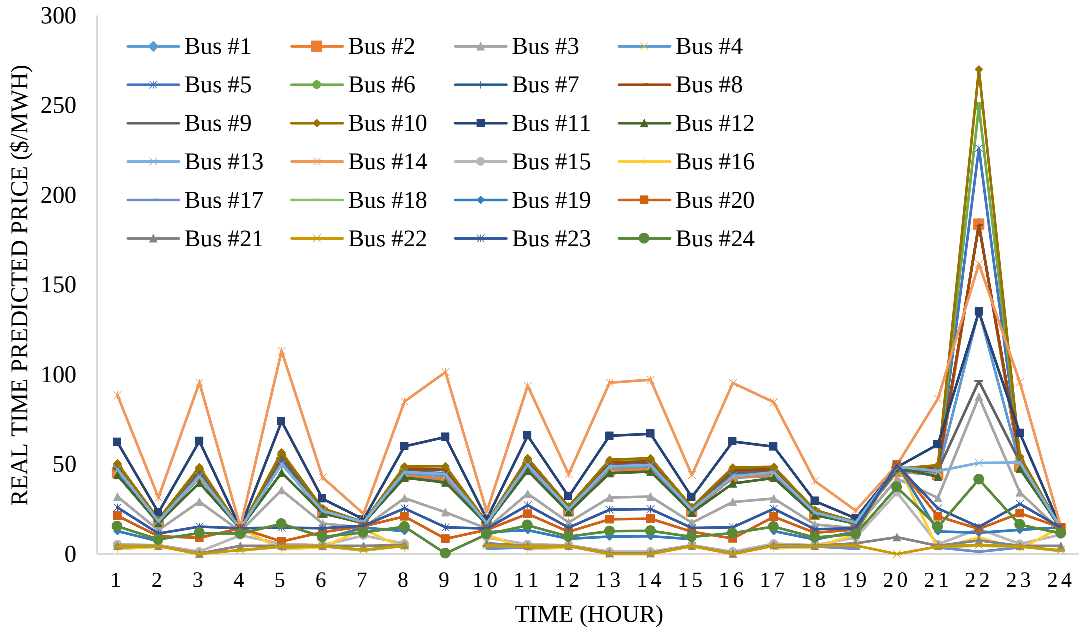


Figure 3.5 Forecasted RT market LMP at different buses and periods.

Forecasted Real-Time LMP at different locations and periods are presented in Figure 3.5. Offer quantities and prices of other generation units are represented in Table 3.5, which are assumed to be the same for all periods. Forecasted loads' bid quantities are depicted in Figure 3.6, and their corresponding predicted bid prices is shown in Figure 3.7. Note that this predicted bid price profile is considered the same for all loads.

We designed 9 different cases to present the effectiveness of the proposed model. The first case is the Deterministic case in which all robustness parameters are zero. In Cases 2 – 6, just one robustness parameter is assumed to be non-zero, and in other Cases (Cases 7 – 9), all robustness parameters are non-zero. Cases 7 – 9 are designed to present the benefit of the proposed robust model in the highly uncertain situation. Table 3.6 summarizes the designed cases.

Table 3.5 Forecasted Offer Quantities and Prices of other Generating Units.

Gen #	$\overline{P}_{tjb}^{G}$ (MW)	λ_{tjb}^{G} ($/MWH)	Location (Bus #)	Gen #	$\overline{P}_{tjb}^{G}$ (MW)	λ_{tjb}^{G} ($/MWH)	Location (Bus #)
G_1	20	13.7	1	G_{17}	12	26.11	15
G_2	20	13.7	1	G_{18}	12	26.11	15
G_3	76	13.32	1	G_{19}	12	26.11	15
G_4	76	13.32	1	G_{20}	155	10.53	15
G_5	20	13.7	2	G_{21}	155	10.53	16
G_6	20	13.7	2	G_{22}	400	5.47	18
G_7	76	13.32	2	G_{23}	400	5.47	21
G_8	76	13.32	2	G_{24}	50	0	22
G_9	100	20.76	7	G_{25}	50	0	22
G_{10}	100	20.76	7	G_{26}	50	0	22
G_{11}	100	20.76	7	G_{27}	50	0	22
G_{12}	197	10.89	13	G_{28}	50	0	22
G_{13}	197	10.89	13	G_{29}	50	0	22
G_{14}	197	10.89	13	G_{30}	155	10.53	23
G_{15}	12	26.11	15	G_{31}	155	10.53	23
G_{16}	12	26.11	15	G_{32}	350	20.72	23

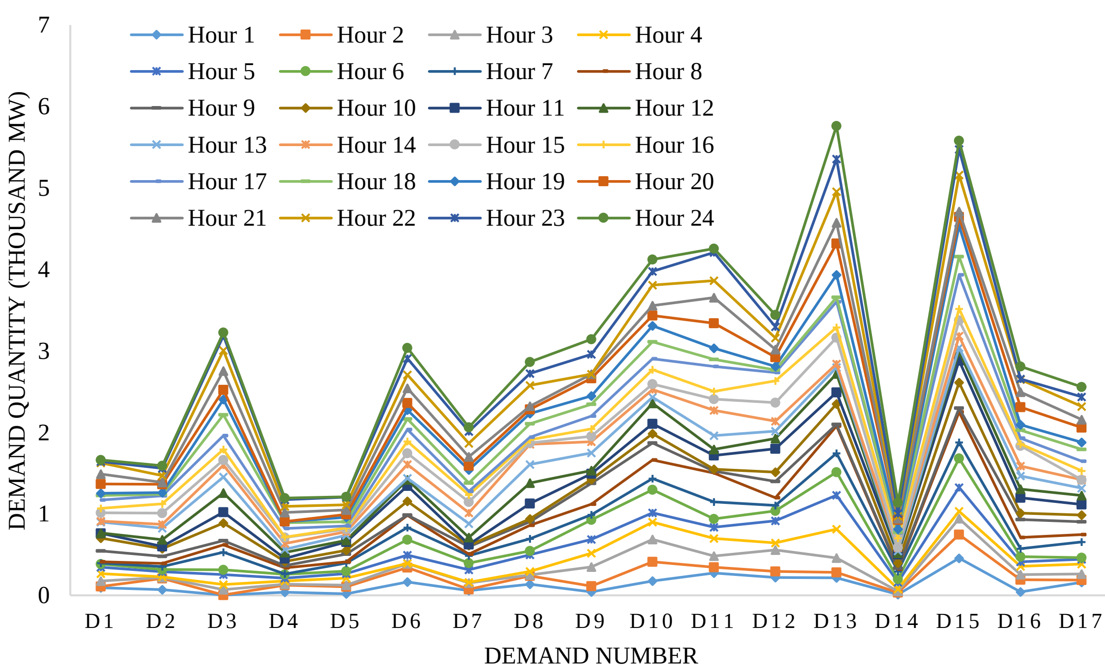


Figure 3.6 Forecasted loads quantities at different periods.

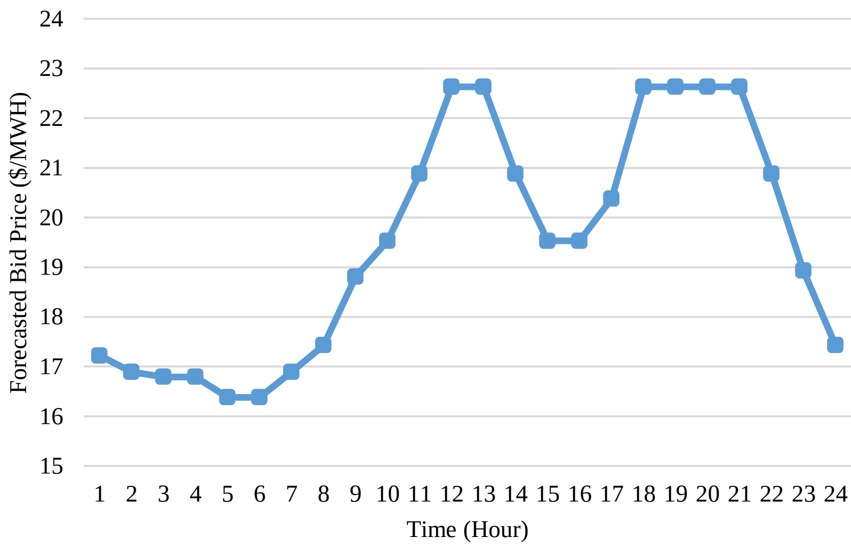


Figure 3.7 Forecasted bid prices for all loads at different periods.

Table 3.6 Different Cases Design for Uncertainties (%).

Uncertainty source	Case 1	Case 2	Case 3	Case 4	Case 5	Case 6	Case 7	Case 8	Case 9
$\boldsymbol{\zeta_n^{RT}}$	0	20	0	0	0	0	10	20	30
$\boldsymbol{\sigma_{jb}^{G}}$	0	0	20	0	0	0	10	20	30
$\boldsymbol{\sigma_{dk}^{D}}$	0	0	0	20	0	0	10	20	30
$\boldsymbol{\tau_{jb}^{G}}$	0	0	0	0	20	0	10	20	30
$\boldsymbol{\tau_{dk}^{D}}$	0	0	0	0	0	20	10	20	30

3.4.2. Results and Discussion. We solved the designed cases, explained in the previous section, with the proposed *Model (5)*. Moreover, for comparison purpose, the Deterministic model results were tested at the worst-case situations. As it is shown in Figure 3.8, the total profit of virtual bidder is always higher than the profit this MP can obtain from the Deterministic model. This is because the Deterministic model results are not applicable in the worst-case scenario and most of the time, they are not cleared in the DA market, which leads to lower profit. Therefore, a risk-averse virtual bidder would prefer to apply the robust-based solution in situations with uncertain sources.

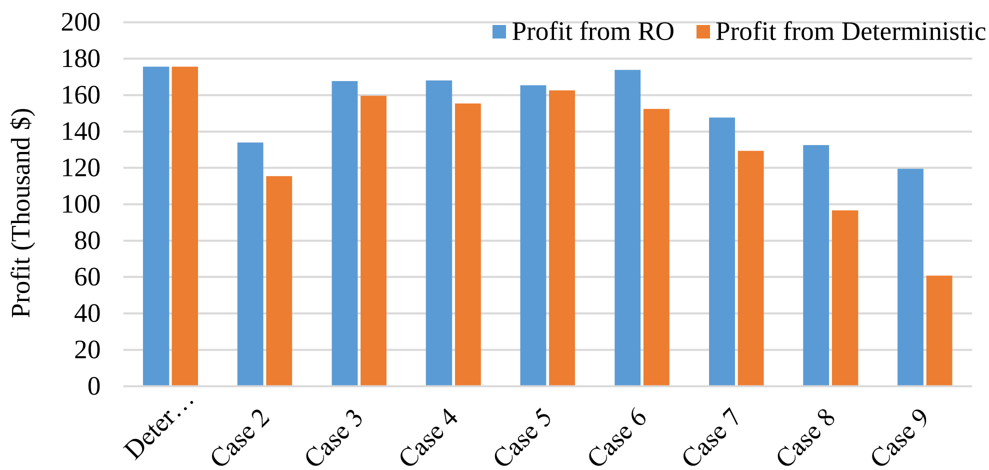


Figure 3.8 Total profit of the virtual bidder using deterministic and robust optimization at the worst-case scenario of different test cases.

All tests were performed on a computer with a 3.2 GHz Intel Core i7 CPU and 32GB of RAM. The models were implemented in AIMMS 4.75.1.0 [83] and solved using CPLEX 12.10 [84]. The number of variables, constraints, and CPU clock times regarding the deterministic model and robust model are summarized in Table 3.7.

Table 3.7 Number of variables, constraints and CPU clock times of the deterministic and robust models.

	Deterministic Model	Robust Model
# Variables	17041	29617
# Constraints	15025	25705
CPU Time	3.1 sec	17.4 sec

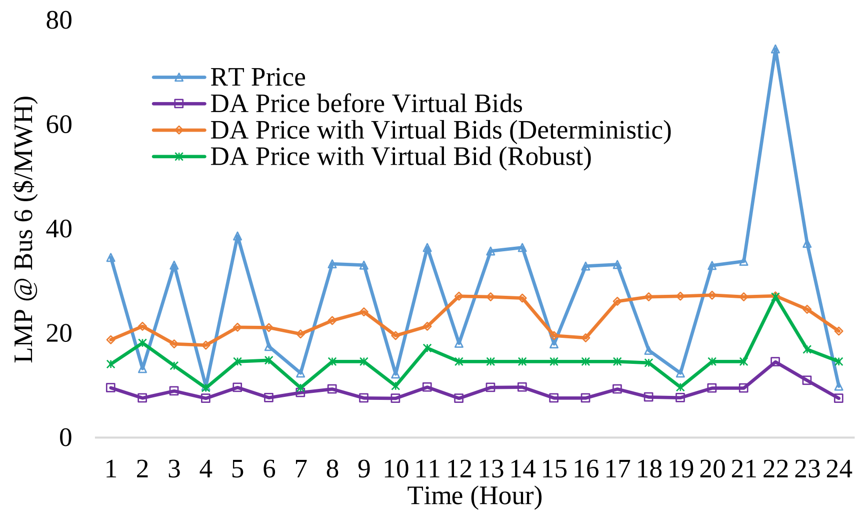
To present the influence of the virtual bids on the DA market prices, DA LMPs at two selected buses where the virtual bidder places its bids (buses 6 and 22), are shown in Figure 3.9. Note that these prices are captured in the worst-case scenario. As seen from Figure 3.9, the predicted RT LMP at bus 6 is higher than the DA LMP before placing the virtual bids. Using the deterministic model, virtual bids cause a reverse divergence between RT and DA LMPs at multiple hours, which results in a negative profit for the virtual bidder. However, there is a reasonable convergence between RT and DA LMPs when the robust optimization results are applied by the virtual bidder. The same situation applies to LMPs at bus 22, except that the predicted RT price is smaller than the DA LMP before virtual bids.

A sensitivity analysis has been done here to find the most critical uncertain parameter which can highly affect the total profit. Therefore, the *Profit Change* is calculated using Equation (3.60) for designed Cases 2 – 6. In each of the cases, only one of the uncertainty parameters is considered. In Equation (3.60), R_d is the profit of Deterministic result in the forecasted scenario, and R_t is the profit of the Deterministic/Robust models' results testing in the worst-case scenario.

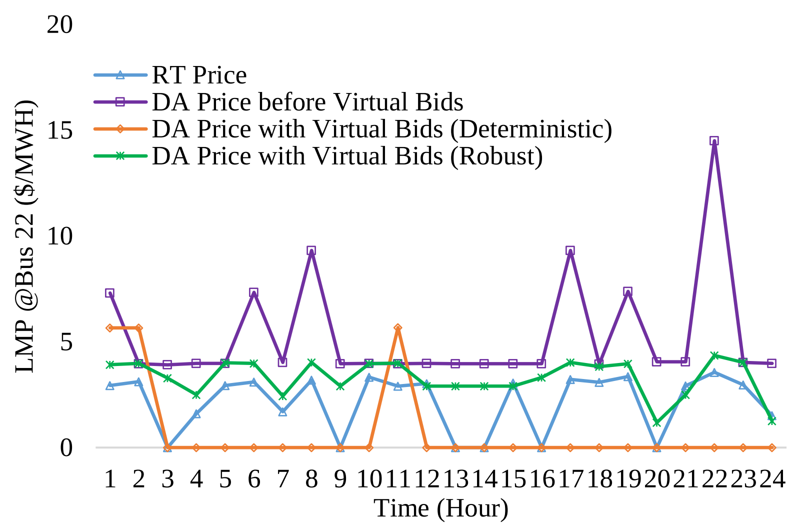
$$Profit\ Change = \frac{|R_d - R_t|}{R_d} \times 100 \tag{3.60}$$

As it is seen in Figure 3.8, the profit obtained from the Deterministic result in the forecasted scenario (Case 1) is \$175,635, while the profit of the virtual bidder is \$133,974 when applying the Robust-based results in the worst-case scenario (Case 2). Thus, the profit change is 23.72% for this designed case.

Figure 3.10 compares the profit changes calculated for Cases 2 – 6 for both deterministic-based and Robust-based results tested at the worst-case scenarios. It is obvious that the higher the profit change is, the greater the impact of the corresponding parameter on the total profit. Therefore, as shown in Figure 3.10, RT LMP has the greatest influence on the total profit of the virtual bidder.



(a)



(b)

Figure 3.9 RT price, DA price before virtual bids, DA price with virtual bids using deterministic model, and DA price with virtual bids using the robust model at bus 6 (a) and bus 22 (b).

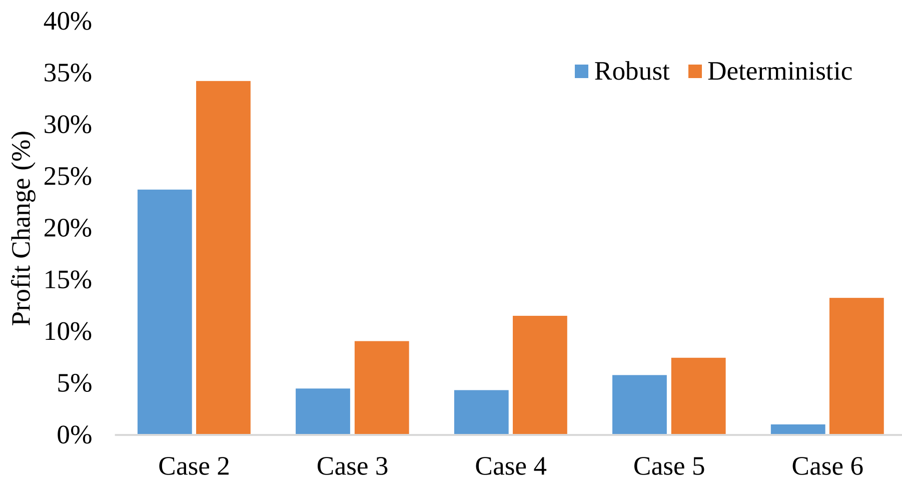


Figure 3.10 Total profit of the virtual bidder using deterministic and robust optimization at the worst-case scenario of different test cases.

In order to observe the performance of the proposed model, this model has been tested with different levels of uncertainty (Cases 7 – 9). As shown in Figure 3.11, the difference between the profits attained from the proposed model and deterministic model results will rise as the level of uncertainty increases. Note that, in these tests, the worst-case scenario was utilized to evaluate the results of the robust and deterministic models. Therefore, the outcome of deterministic model results may change when the uncertainty level changes.

$$Improvement\ \ in\, profit = \frac{|R_r - R'_d|}{R_r} \times 100 \tag{3.61}$$

The $improvement\ in\ profit$, which is calculated by Equation (3.61), represents the advantages of applying the proposed model specifically for the risk-averse virtual bidders who consider the higher confidence interval for the uncertain parameters. Figure 3.11 shows that the improvement in profit reaches 50% when the virtual bidder chooses 0.3 for the robustness parameters in his/her decision-making process. It clearly demonstrates the benefits of the proposed model. In Equation (3.61), R_r is the profit of the robust-based model, and R'_d is the profit of the Deterministic model results testing at the worst-case scenario.

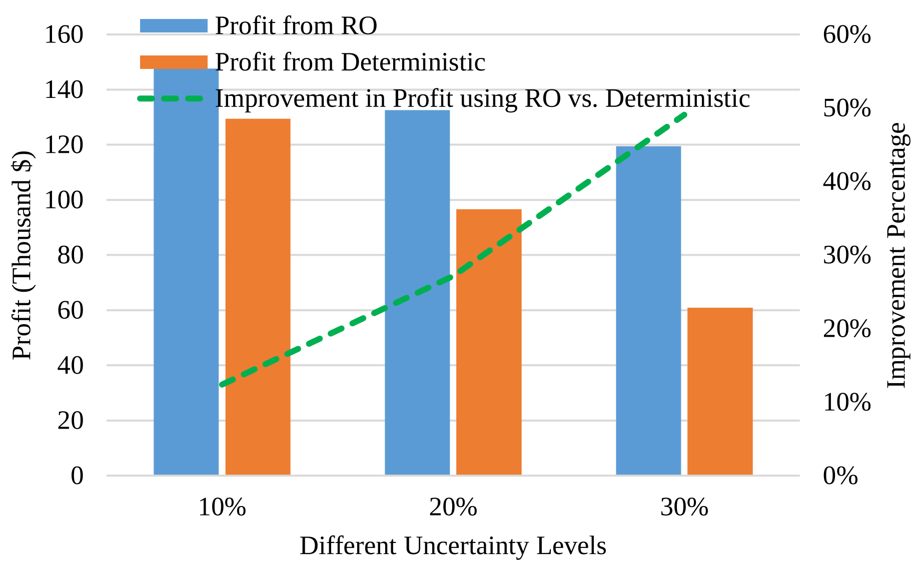


Figure 3.11 Profit comparison between the deterministic model and robust model results tested at the worst-case scenario with different level of uncertainty.

3.5. SECTION SUMMARY

This section employs RO to develop a DA market bidding strategy for virtual bidders. The proposed model allows the virtual bidder to maximize its profit by considering its flexibility of being either generation or load at different locations of the system. RO is employed to handle the uncertainties associated with rivals' offer/bids and RT market LMPs. Furthermore, based on the KKT conditions, SDT and big-M method, the proposed max-min bi-level model is equivalently linearized and transformed into a MILP, making it solvable by accessible commercial solvers. As the lower-level subproblem of the model represents the quasi DA market, a virtual bidder can mimic the market clearing process and can appropriately make bidding decisions to its best interest. Therefore, through the bid price, a virtual bidder can effectively compromise between the amount of cleared virtual bids and the affected price difference between the DA and RT markets considering the uncertainties of other MPs' strategies and RT market LMPs. Numerical results and sensitivity analysis show that RT LMP is the most critical uncertain parameter that the virtual bidder needs to consider in his/her decision-making procedure. Moreover, as compared to using the deterministic model, a risk-averse virtual bidder can always make more profit at the worst-case scenario employing the proposed model, and the improvement in profits increases dramatically as the uncertainty level increases

4. BIDDING STRATEGY FOR PHYSICAL MARKET PARTICIPANTS WITH VIRTUAL BIDDING CAPABILITY

4.1. BACKGROUND

Market structures can be divided into two groups based on how perfectly and imperfectly a market is competitive from a microeconomics standpoint. In a market with perfect competition, there are many producers and customers competing for the same homogenous product, and the market price is set only by supply and demand, and no company can affect the market price by altering its bidding strategy. However, due to imperfect competition, some market participants (MPs) have the ability to sway market prices in favor of their own interests [5, 37]. Aside from the purely financial players, physical MPs can also take part in virtual bidding in power markets. However, due to their interdependence with the physical assets they own, their optimal approach may differ greatly from that of purely financial players. For instance, when the RT market price is expected to be higher than the DA market price, virtual DEC can provide a positive virtual profit. However, it may increase the DA market price which may cause the reduction of cleared physical generation and therefore decrease the profit from physical generation. Therefore, the decision-making of physical MP with virtual bidding capabilities is an innovative and difficult topic that requires more investigation.

The following aspects need to be included into the decision-making process for a physical MP that is also capable of conducting virtual transactions. To begin, the objective is not to maximize any one part of the profit; rather, it is to maximize the whole profit, which comprises the profit from both the physical generation and the virtual transaction. Second, the prices of DA on the market might be affected by virtual transactions (either INC or DEC), which could then have an effect on the amount of money made from the physical generation. Third, the physical generation may also have an effect on the price of DA and, as a consequence, alters the difference in price between DA and RT, which may lead to variations in the profit gained through virtual transactions. Therefore, an effective strategy for placing bids should make it possible for the MP to wisely control the effect that it has on the DA price, with the ultimate objective of optimizing the total profit. Besides, the decision-making process of a physical MP with virtual bidding capability is subject to two major uncertainties: the forecasted price of the RT market, and the price of the DA market, which is influenced not only by the virtual bids and offers of the physical MP itself, but also by the bidding strategy of other MPs attending in the DA market. In order to develop an optimal bidding strategy for physical MP with virtual bidding capability and at the same time consider the uncertainties in DA market price and RT market price forecast, this section proposes a risk-controlled bi-level optimization model to maximize the total profit for the appropriate risk level. The upper-level subproblem aims to maximize the profit of this MP whose income is measured according to the cleared DA market price obtained at the lower-level subproblem which represents the market clearing procedure. The outputs of lower-level subproblem include cleared energy, cleared virtual transactions and the DA market LMP, are turned back to the upper-level subproblem. Besides, to handle the aforementioned uncertainties, this subproblem incorporates scenario-based uncertainties of rivals' strategies and RT market prices. Finally, the conditional value-at-risk (CVaR) is employed to empirically estimate the risk of payoff associated with various strategies.

4.2. PROBLEM DESCRIPTION

The overall structure of the problem is described in this subsection.

4.2.1. Bidding Strategy of Physical MP With Virtual Bidding Capability.

During the day before the operating day, the DA market is cleared on an hourly basis, while the RT market is cleared on a five-minute basis; nevertheless, its settlement is executed based on the average of twelve five-minute time slots [51]. In real world, there is often a discrepancy between the prices of DA and RT markets; hence, a physical MP who is able to participate in virtual bidding has the capability to arbitrage the price disparities by engaging in virtual transactions.

In theory, a physical MP that holds a large market share has the ability to influence the DA market LMP and, as a result, maximize the profits generated by its physical generation. Nonetheless, this adjustment may make the price gap between DA and RT less significant, which would mean a smaller profit potential for the virtual transaction. Therefore, in order for the MP to maximize its profit, it is necessary for them to find a balance not only between the cleared power and the DA market LMP, but also between the cleared power and the influence that it has on the DA/RT price spread, while monitor the probable risk of profit volatility.

4.2.2. Uncertainty Characterization. When determining its offers and bids, a MP is confronted with a number of uncertainties, including the strategy of its competitors and the RT market prices. In order to cope with these uncertainties, a variety of scenarios have been established. These scenarios represent the many possible realizations of the unknown variables and the probability associated with each of those realizations. For the purpose of the problem formulation presented in this study, two distinct scenario sets are specified:

1) Day-Ahead market scenarios which denote the different strategies of other generators/demands

2) Real-Time market scenarios which denote the different RT market price predictions.

4.2.3. Risk Modeling. Because of the aforementioned unpredictability of the situation, it is possible that certain MPs will not be ready to adopt a strategy that has a high probability of resulting in significant profit volatility. As a result, the Conditional Value-at-Risk (CVaR) measure has been implemented; this gives market participants the ability to keep track of the risks that are associated with the offers and bids they make. This metric is linear and easy to integrate into the optimization problem [85].

4.2.4. Model Description. In this section, the optimal bidding strategy of a physical MP with the virtual bidding capability in the DA market is formulated by means of a stochastic bi-level optimization model. The upper-level subproblem of the proposed model illustrates the MP’s payoff maximization problem, and the evaluation of market clearing procedure under various scenarios, is performed in the lower-level subproblems. The upper-level and lower-level subproblems are connected by their respective decision variables. The decision variables of the upper-level subproblem which consist of the MP's offers/bids to sell/purchase physical power or virtual bids in/from the DA market, are transferred to the lower-level subproblem as parameters. The decision variables of the lower-level subproblem include cleared power sold (purchased) by all generating units (demands), and wholesale energy prices, which are returned to the upper-level problem for MP profit calculation

4.3. MATHEMATICAL FORMULATION

In order to make the model more understandable, a deterministic bi-level model of the examined bidding strategy problem will first be described. This model will assume that there are no model uncertainties. Next, the stochastic bi-level model is improved by include a modeling of uncertainty and risk.

4.3.1. Deterministic Bi-Level Model. The bidding strategy of a physical MP with virtual bidding capability in the DA market can be formulated using the bi-level optimization model as follows:

A) Upper-Level

$$\underset{\substack{\gamma_{tik}^{G},P_{tik}^{G}\\ ,\gamma_{tv},\overline{V}_{tv}}}{\text{Min}} \sum_{tik} \lambda_{tik}^{G} P_{tik}^{G} - \sum_{t(i\in\psi_n)k} \lambda_{tn}^{DA} P_{tik}^{G} - \sum_{t(v\in\psi_n)} \lambda_{tn}^{DA} V_{tv} + \sum_{t(v\in\psi_n)} \lambda_{tn}^{RT} V_{tv} \tag{4.1}$$

Subject to:

$$\sum_{k} P_{(t+1)ik}^{G} - \sum_{k} P_{tik}^{G} \le R_{i}^{UP}, \quad \forall t, \forall i \tag{4.2}$$

$$\sum_{k} P_{tik}^{G} - \sum_{k} P_{(t+1)ik}^{G} \le R_{i}^{LO}, \quad \forall t, \forall i \tag{4.3}$$

$$\sum_{tv} Proxy_{tv} V_{tv} \le B, \tag{4.4}$$

$$-V_{tv}^{max} \le \overline{V}_{tv} \le V_{tv}^{max} \qquad \forall t, \forall v \tag{4.5}$$

B) Lower-level:

$$V_{tv}, P_{tik}^{G} \in arg \left\{ \underset{V_{tv},P_{tik}^{G},P_{tjk}^{R},P_{tdk}^{D}}{\text{Minimize}} \sum_{tv} \gamma_{tv} V_{tv} + \sum_{tik} \gamma_{tik}^{G} P_{tik}^{G} + \sum_{tjk} \lambda_{tjk}^{R} P_{tjk}^{R} \right.$$
$$\left. - \sum_{tdk} \lambda_{tdk}^{D} P_{tdk}^{D} \right. \tag{4.6}$$

Subject to:

$$\sum_{v} V_{tv} + \sum_{ik} P_{tik}^{G} + \sum_{jk} P_{tjk}^{R} = \sum_{dk} P_{tdk}^{D} \;:\; \lambda_{tf}^{DA}, \qquad \forall t \tag{4.7}$$

$$-\overline{V}_{tv} \le V_{tv} \le \overline{V}_{tv} \qquad : \overline{\rho}_{tv}^{V}, \underline{\rho}_{tv}^{V}, \quad \forall t, \forall v \tag{4.8}$$

$$0 \le P_{tik}^{G} \le \overline{P}_{tik}^{G} \qquad : \overline{\rho}_{tik}^{G}, \underline{\rho}_{tik}^{G}, \quad \forall t, \forall i, \forall k \tag{4.9}$$

$$0 \le P_{tjk}^{R} \le \overline{P}_{tjk}^{R} \qquad : \overline{\rho}_{tjk}^{R}, \rho_{tjk}^{R}, \quad \forall t, \forall j, \forall k \tag{4.10}$$

$$0 \le P_{tdk}^{D} \le \overline{P}_{tdk}^{D} \qquad : \overline{\rho}_{tdk}^{D}, \rho_{tdk}^{D}, \quad \forall t, \forall d, \forall k \tag{4.11}$$

$$-\overline{C}_{l} \le \sum_{n} PTDF_{nl} \left(\sum_{(v \in \psi_n)} V_{tv} + \sum_{(i \in \psi_n)k} P_{tik}^{G} \sum_{(j \in \psi_n)k} P_{tjk}^{R} - \sum_{(d \in \psi_n)k} P_{tdk}^{D} \right) \le \overline{C}_{l} \quad : \underline{\vartheta}_{tl}, \overline{\vartheta}_{tl} \quad \forall t, \forall l \tag{4.12}$$

$$\lambda_{tn}^{DA} = \lambda_{tf}^{DA} - \sum_{l} PTDF_{nl} \left(\overline{\vartheta}_{tl} - \underline{\vartheta}_{tl} \right) \qquad \forall t, \forall n \tag{4.13}$$

The upper-level subproblem (4.1) – (4.5) represents the profit maximization of the physical MP with virtual bidding capability, and the lower-level subproblem (4.6) – (4.13) represents the DA market clearing process. Note that the notations on the right side of the lower-level constraints represent the dual variables of those constraints. The objective function (4.1) consists of four terms: the first two terms ($\sum_{tik} \lambda_{tik}^{G} P_{tik}^{G} - \sum_{t(i \in \psi_n)k} \lambda_{tn}^{DA} P_{tik}^{G}$) represent the minus of profits of actual generation in the DA market and the second two terms ($-\sum_{t(v \in \psi_n)} \lambda_{tn}^{DA} V_{tv} + \sum_{t(v \in \psi_n)} \lambda_{tn}^{RT} V_{tv}$) are the minus of profits of virtual bids which can be obtained by participating in DA and RT markets. Constraints (4.2) and (4.3) express the ramp-up/down limits of the physical generating units. Constraint (4.4) limits the virtual energy transaction according to its virtual proxy.

Constraint (4.5) imposes power limits that this MP can trade as virtual transactions in the DA market.

The cleared power V_{tv} and P_{tik}^{G} are part of the feasible region specified by the lower-level subproblem (4.6) – (4.13). The objective function (4.6) minimizes the negative of the social welfare. Constraint (4.7) represents the generation-load balance for the whole system, and the dual variable of this constraint denotes the system-wide DA market price (λ_{tf}^{DA}). Constraints (4.8) – (4.10) define the power limits for virtual transaction, physical generation of strategic MP and other nonstrategic generators, respectively. Constraint (4.11) represents the demand limits. Transmission line capacity limits are denoted by constraint (4.12). Constraint (4.13) represents the DA market LMP at bus n and time t. Note that $(i, j, d, v) \in \psi_n$ identifies that these generators/demands are located at bus n and offers/bids from this bus.

Solution Methodology: To convert the bi-level optimization problem described in Subsection 4.3.1 into a single level problem, the lower-level linear optimization problem is replaced by its KKT optimality conditions. The obtained single-level problem, which is known as Mathematical Problem with Equilibrium Constraints (MPEC), is illustrated as follows.

$$\underset{\substack{\gamma_{tik}^{G}, P_{tik}^{G}, \\ \gamma_{tv}, V_{tv}}}{\text{Min}} \sum_{tik} \lambda_{tik}^{G} P_{tik}^{G} - \sum_{t(i \in \psi_n)k} \lambda_{tn}^{DA} P_{tik}^{G} - \sum_{t(v \in \psi_n)} \lambda_{tn}^{DA} V_{tv} + \sum_{t(v \in \psi_n)} \lambda_{tn}^{RT} V_{tv} \tag{4.14}$$

Subject to:

Constraints (4.2) - (4.5) (4.15)

$$\gamma_{tik}^{G} - \lambda_{tn}^{DA} + \overline{\rho}_{tik}^{G} - \underline{\rho}_{tik}^{G} = 0, \qquad \forall t, \forall i \in \psi_n, \forall k \tag{4.16}$$

$$\gamma_{tv} - \lambda_{tn}^{DA} + \overline{\rho}_{tv}^{V} - \underline{\rho}_{tv}^{V} = 0, \qquad \forall t, \forall v \in \psi_n \tag{4.17}$$

$$\lambda_{tjk}^{R} - \lambda_{tn}^{DA} + \overline{\rho}_{tjk}^{R} - \underline{\rho}_{tjk}^{R} = 0, \qquad \forall t, \forall j \in \psi_n, \forall k \tag{4.18}$$

$$-\lambda_{tdk}^{D} + \lambda_{tn}^{DA} + \overline{\rho}_{tdk}^{D} - \underline{\rho}_{tdk}^{D} = 0, \quad \forall t, \forall d \in \psi_n, \forall k \tag{4.19}$$

Constraints (4.7) and (4.13) (4.20)

$$0 \le V_{tv} + \overline{V}_{tv} \perp \underline{\rho}_{tv}^{V} \ge 0, \qquad \forall t, \forall v \tag{4.21}$$

$$0 \le \overline{V}_{tv} - V_{tv} \perp \overline{\rho}_{tv}^{V} \ge 0, \qquad \forall t, \forall v \tag{4.22}$$

$$0 \le P_{tik}^{G} \perp \underline{\rho}_{tik}^{G} \ge 0, \qquad \forall t, \forall i, \forall k \tag{4.23}$$

$$0 \le \overline{P}_{tik}^{G} - P_{tik}^{G} \perp \overline{\rho}_{tik}^{G} \ge 0, \qquad \forall t, \forall i, \forall k \tag{4.24}$$

$$0 \le P_{tjk}^{R} \perp \underline{\rho}_{tjk}^{R} \ge 0, \qquad \forall t, \forall j, \forall k \tag{4.25}$$

$$0 \le \overline{P}_{tjk}^{R} - P_{tjk}^{R} \perp \overline{\rho}_{tjk}^{R} \ge 0, \qquad \forall t, \forall j, \forall k \tag{4.26}$$

$$0 \le P_{tdk}^{D} \perp \underline{\rho}_{tdk}^{D} \ge 0, \qquad \forall t, \forall d, \forall k \tag{4.27}$$

$$0 \le \overline{P}_{tdk}^{D} - P_{tdk}^{D} \perp \overline{\rho}_{tdk}^{D} \ge 0, \qquad \forall t, \forall d, \forall k \tag{4.28}$$

$$0 \le \overline{C}_l + \sum_{n} PTDF_{nl} \left(\sum_{(v \in \psi_n)} V_{tv} + \sum_{(i \in \psi_n)k} P_{tik}^{G} + \sum_{(j \in \psi_n)k} P_{tjk}^{R} - \sum_{(d \in \psi_n)k} P_{tdk}^{D} \right) \perp \underline{\vartheta}_{tl} \ge 0 \qquad \forall t, \forall l \tag{4.29}$$

$$0 \le \overline{C}_l - \sum_{n} PTDF_{nl} \left(\sum_{(v \in \psi_n)} V_{tv} + \sum_{(i \in \psi_n)k} P_{tik}^{G} + \sum_{(j \in \psi_n)k} P_{tjk}^{R} - \sum_{(d \in \psi_n)k} P_{tdk}^{D} \right) \perp \overline{\vartheta}_{tl} \ge 0 \qquad \forall t, \forall l \tag{4.30}$$

Constraints (4.16) – (4.19) are the set of partial derivatives of the Lagrangian function of the lower-level subproblem regarding to the lower-level decision variables.

Constraints (4.20) are the primal equality constraints of the lower-level subproblem, and the remaining constraints are the complementarity constraints. The resulted model is a single-level nonlinear problem, whose nonlinearity comes from three terms: terms $\lambda_{tn}^{DA} P_{tik}^{G}$ and $\lambda_{tn}^{DA} V_{tv}$ in the objective function (4.14) and the complementarity constraints (4.21) – (4.30). The nonlinear terms in (4.14) can be translated to their equivalent linear expressions applying the strong duality theorem (SDT) [39]. Furthermore, the Fortuny-Amat Transformation technique [86] is used to replace the complementarity constraints with their equivalent mixed integer linear terms.

4.3.2. Stochastic Bi-Level Model with Uncertainty and Risk Modeling.

Bidding strategy of the intended MP is affected by the uncertainties of other MPs' strategies and the RT market prices. These uncertainties can be incorporated into the main problem ((4.1) - (4.13)) by employing a sets of scenarios, each of which represents the realization of different uncertain parameters. In this modeling, the probability distribution functions (PDF) of all uncertain parameters are assumed to be known or estimated based on historical information. Adding the Conditional Value-at-Risk (CVaR) measure to control the profit risk, the resulted formulation will be as follows.

In this formulation all variables are $\Delta = \{\gamma_{tv}, V_{tvs}, \overline{V}_{tv}, VaR, \eta_{sw}, \gamma_{tik}^{G}, P_{tiks}^{G},$ $\lambda_{tfs}^{DA},$: $\overline{\rho}_{tvs}^{V}$, $\underline{\rho}_{tvs}^{V}, \overline{\rho}_{tiks}^{G}$, $\underline{\rho}_{tiks}^{G}$, $\overline{\rho}_{tjks}^{R}$, ρ_{tjks}^{R}, $\overline{\rho}_{tjks}^{R}$, ρ_{tjks}^{R}, $\overline{\rho}_{tdks}^{D}$, ρ_{tdks}^{D}, $\underline{\vartheta}_{tls}$, $\overline{\vartheta}_{tls}$ *and* λ_{tns}^{DA} $\}$ and the binary variables created during applying Fortuny-Amat (Big-M) transformation. The objective function (4.31) is the negative of the expected profit and Π_s represents the probability associated with scenario s. RT market price uncertainty has been represented in the fourth term of the objective function, in which τ_w is the probability of scenarios associated with RT market price scenarios. The last term of the objective function (4.31) is CVaR. Weighting parameter β is employed to trade off between the expected profit and CVaR. The lower β is, the more risk-taker the MP is. However, risk-averse MP accepts the higher value of β. It means if β is large enough (close to 1), the MP neglects its expected profit but guarantees the minimum profit for a given confidence level α.

A) Upper-Level

$$\underset{\Delta}{\text{Maximize}}(1-\beta)\sum_{s}\Pi_s\left(\sum_{t(i\in\psi_n)k}\lambda_{tns}^{DA}P_{tiks}^{G}+\sum_{t(v\in\psi_n)}\lambda_{tns}^{DA}V_{tvs}-\sum_{tik}\lambda_{tik}^{G}P_{tiks}^{G}\right.$$
$$\left.-\sum_{t(i\in\psi_n)w}\tau_w\lambda_{tnw}^{RT}V_{tvs}\right)+\beta\left(VaR-\frac{1}{1-\alpha}\sum_{sw-}\Pi_s\,\tau_w\eta_{sw}\right) \tag{4.31}$$

Subject to:

$$\sum_{k}P_{(t+1)iks}^{G}-\sum_{k}P_{tiks}^{G}\leq R_i^{UP},\quad \forall t,\forall i,\forall s \tag{4.32}$$

$$\sum_{k}P_{tiks}^{G}-\sum_{k}P_{(t+1)iks}^{G}\leq R_i^{LO},\quad \forall t,\forall i,\forall s \tag{4.33}$$

$$\sum_{tv}Proxy_{tv}V_{tvs}\leq B,\qquad \forall s \tag{4.34}$$

$$-V_{tv}^{max}\leq\overline{V}_{tv}\leq V_{tv}^{max}\qquad \forall t,\forall v,\forall s \tag{4.35}$$

$$VaR-\left(\sum_{t(i\in\psi_n)k}\lambda_{tns}^{DA}P_{tiks}^{G}+\sum_{t(v\in\psi_n)}\lambda_{tns}^{DA}V_{tvs}-\sum_{tik}\lambda_{tik}^{G}P_{tiks}^{G}\right.$$
$$\left.-\sum_{t(v\in\psi_n)}\lambda_{tnw}^{RT}V_{tvs}\right)\leq\eta_{sw}\qquad \forall s,\forall w \tag{4.36}$$

$$\eta_{sw}\geq 0,\qquad \forall s,\forall w \tag{4.37}$$

B) Lower-level:

$$(V_{tvs}, P^G_{tiks}) \in arg\left\{\underset{P^G_{tiks}, V_{tvs}, P^R_{tjks}, P^D_{tdks}}{\text{Minimize}} \sum_{tv} \gamma_{tv} V_{tvs} + \sum_{tik} \gamma^G_{tik} P^G_{tiks} \right.$$

$$+ \sum_{tjk} \lambda^R_{tjks} P^R_{tjks} - \sum_{tdk} \lambda^D_{tdks} P^D_{tdks} \tag{4.38}$$

Subject to:

$$\sum_{v} V_{tvs} + \sum_{ik} P^G_{tiks} + \sum_{jk} P^R_{tjks} = \sum_{dk} P^D_{tdks} \quad : \lambda^{DA}_{tfs}, \qquad \forall t, \forall s \tag{4.39}$$

$$-\overline{V}_{tv} \le V_{tvs} \le \overline{V}_{tv} \quad : \overline{\rho}^V_{tvs}, \underline{\rho}^V_{tvs}, \quad \forall t, \forall v, \forall s \tag{4.40}$$

$$0 \le P^G_{tiks} \le \overline{P}^G_{tik} \quad : \overline{\rho}^G_{tiks}, \underline{\rho}^G_{tiks}, \quad \forall t, \forall i, \forall k, \forall s \tag{4.41}$$

$$0 \le P^R_{tjks} \le \overline{P}^R_{tjk} \quad : \overline{\rho}^R_{tjks}, \rho^R_{tjks}, \quad \forall t, \forall j, \forall k, \forall s \tag{4.42}$$

$$0 \le P^D_{tdks} \le \overline{P}^D_{tdk} \quad : \overline{\rho}^D_{tdks}, \rho^D_{tdks}, \quad \forall t, \forall d, \forall k, \forall s \tag{4.43}$$

$$-\overline{C}_l \le \sum_n PTDF_{nl}\left(\sum_{(v\in\psi_n)} V_{tvs} + \sum_{(i\in\psi_n)k} P^G_{tiks} \sum_{(j\in\psi_n)k} P^R_{tjks} \right.$$

$$\left. - \sum_{(d\in\psi_n)k} P^D_{tdks} \right) \le \overline{C}_l \quad : \underline{\vartheta}_{tls}, \overline{\vartheta}_{tls} \quad \forall t, \forall l, \forall s \tag{4.44}$$

$$\lambda^{DA}_{tns} = \lambda^{DA}_{tfs} - \sum_l PTDF_{nl}\left(\overline{\vartheta}_{tls} - \underline{\vartheta}_{tls}\right) \quad \forall t, \forall n, \forall s \tag{4.45}$$

Constraints (4.36) and (4.37) are used to compute the CVaR [85]. All other constraints are similar to the deterministic model, while the lower-level subproblem is solved for each scenario s. The procedure of constructing the MPEC and MILP for problem ((4.31) – (4.45)) is completely similar to the deterministic model.

4.4. CASE STUDY

The proposed models have been tested on systems of different sizes, and for different conditions (including uncongested and congested conditions). For demonstration purpose, two IEEE standard systems (IEEE 14-bus test system and IEEE 39-bus test system) have been studied in an uncongested condition. Detailed data and results are illustrated as follows.

4.4.1. Data and Setups. Systems' data used in this section such as generation capacities, maximum load quantities, transmission line capacities, and etc. have been taken from [87, 88]. Moreover, forecasted offers/bids prices of generators/loads are obtained from [39], and have been slightly modified to match the assumptions made in this section. The IEEE 14-bus test system has 14 buses, 5 generators, 11 loads, and 20 transmission lines [88]. Modifications and additional parameters have been made to the system for better illustration. The generators' data is summarized in Table 4.1. It is assumed that generators submit two-block offer curves for each hour. The two-block offer generations are shown by $\overline{P}_1$ and $\overline{P}_2$, and the corresponding marginal costs are depicted by λ_1 and λ_2. RU/RD represents the generator ramp up and ramp down rate. We consider that a strategic MP has two generators G1 and G3 located at buses 1 and 3 with installed capacities of 182.4 MW and 100 MW, respectively.

Table 4.2 and Table 4.3 display the demand bids and the corresponding bid prices of the two blocks, respectively. For the sake of simplicity, the similar 24-hour bid price profile is employed for all loads.

Table 4.1 Generators Data.

	G1	G2	G3	G4	G5
Bus #	1	2	3	6	8
Capacity (MW)	182.4	130	100	100	100
$\overline{P}_1$ (MW)	150.2	99	55	50	55
$\overline{P}_2$ (MW)	32.2	41	45	50	45
λ_1 ($/MWh)	10.37	10.08	11.32	11.71	19.32
λ_2 ($/MWh)	11.41	10.97	13.19	14.93	22.19
RU/RD (MW/h)	150	120	100	80	90

Table 4.2 Demand Quantity (MW).

Load #	Block 1	Block 2	Load #	Block 1	Block 2
1	21.7	20.5	7	9	7
2	94.2	88.4	8	3.5	6
3	47.8	32.5	9	6.1	12.1
4	7.6	10.1	10	13.5	15
5	11.2	14.3	11	14.9	21.2
6	29.5	30			

Table 4.3 Demand Bid price ($/MWh).

Hour	Block 1	Block 2	Hour	Block 1	Block 2
1	17.43	16.79	13	25.00	20.61
2	17.25	16.38	14	24.97	20.38
3	17.22	16.32	15	20.38	18.93
4	17.22	16.32	16	20.38	18.93
5	16.89	16.13	17	20.88	19.53
6	16.89	16.13	18	25.00	20.61
7	17.25	16.38	19	25.00	20.61
8	17.94	17.22	20	25.00	20.61
9	19.23	18.15	21	25.00	20.61
10	20.38	18.93	22	24.97	20.38
11	24.97	20.38	23	19.53	18.34
12	25.00	20.61	24	17.94	17.22

Power Transfer distribution Factors (PTDFs) of the IEEE 14-bus test system is obtained from MATPOWER [88]. Forecasted real-time market prices are obtained through simulation and shown in Table 4.4. It is worth mentioning that the price forecast is for an uncongested system and the forecast will change for congested systems.

Table 4.4 Predicted RT market price ($/MWh).

Hour	Price	Hour	Price
1	15.79	13	19.61
2	15.38	14	19.38
3	15.32	15	19.43
4	15.32	16	19.43
5	15.13	17	20.03
6	15.13	18	21.11
7	15.38	19	21.11
8	16.22	20	21.11
9	17.15	21	21.11
10	17.93	22	20.88
11	19.38	23	18.84
12	19.61	24	17.72

Three different case studies have been designed to test the Deterministic Model and Stochastic Model. Different conditions, including uncongested and congested systems, have been tested, and the results for uncongested system are presented for illustration:

- Case 1: All MPs offer their marginal costs, and the strategic MP does not have virtual bidding capability.
- Case 2: Strategic MP offers strategically without virtual bidding capability while other MPs offer their marginal costs.
- Case 3: Strategic MP offers strategically with virtual bidding capability while other MPs offer their marginal costs.

4.4.2. Results for Deterministic Condition. The total cleared power and total profits of the strategic MP for the three cases are depicted in Figure 4.1. It shows that, in comparison to Case 1, where all MPs, including the strategic MP put in their marginal costs as offer prices, this strategic MP makes significantly higher profits in Case 2.

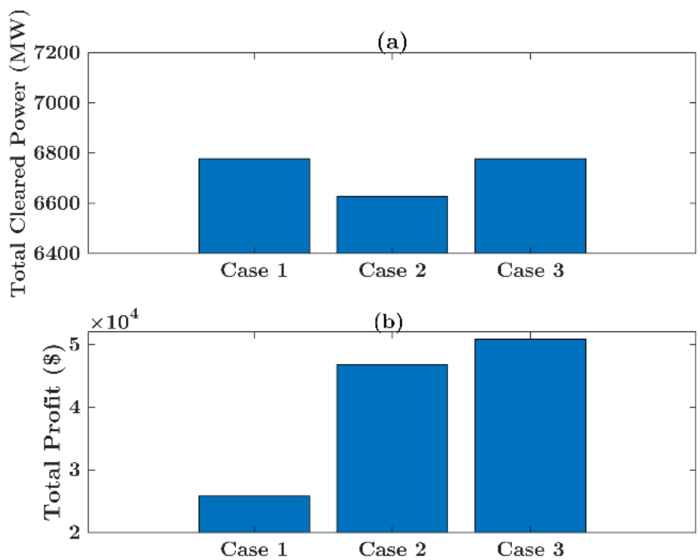


Figure 4.1 Results of the strategic MP in the IEEE 14-bus system. a) Total cleared power and b) Total profits of MP.

In Case 2, the MP offers a strategically determined higher price so that the market clearing price is increased, as shown in Figure 4.2(a). Although the cleared power is reduced, the profit increases. In Case 3, the presence of virtual transactions makes the decision-making process more complicated for the strategic MP since virtual transactions may change the DA market prices and subsequently alter the DA/RT price which affects the virtual transaction profit, and the changed DA price has a direct impact on physical generation profit. Therefore, the strategic MP needs to make a compromise between the physical generation profit and the virtual transaction profit through a delicate balance between the amount of physical/virtual transactions and its impact on DA prices. In comparison to Case 2, more physical generation power of the strategic MP is cleared in Case 3, leading to higher profit for the following reasons:

A) From hour 1 to hour 10, the predicted RT price is lower than the DA price in Case 2, as illustrated in Figure 4.2(a). For virtual transaction without physical generation, the virtual transaction would always choose to act as a virtual generation (INC) in order to make virtual transaction profit. For virtual transactions with physical generation, which is the focus of the work, the MP may choose a different strategy because virtual generation can cause a negative impact on the physical generation profit through its impact on DA prices. In this case study, the strategic MP chooses to bid in as a virtual demand (of 6.3 MW) instead of virtual generation and manages to keep the DA/RT price difference unchanged. Although the virtual demand leads to a negative virtual transaction profit, the strategic MP's generation increases as a result of the virtual demand, and the physical generation profit increases more than the loss in virtual transaction profit, resulting in an increase of the net profit.

B) From hour 11 to hour 14, the predicted RT prices are slightly higher than the DA prices in Case 2 (as seen in Figure 4.2(a)), leaving small room to make virtual transaction profit alone. The strategic MP decides to bid virtual demand in large quantity which substantially increases the DA prices. As the DA prices become higher than the RT prices, it incurs significant loss to the virtual transaction profit. However, the negative virtual transaction profit is offset by the much-increased physical generation profit (as seen in Figure 4.3 (a)) that benefits from increased DA prices. As a result, the total profit has increased.

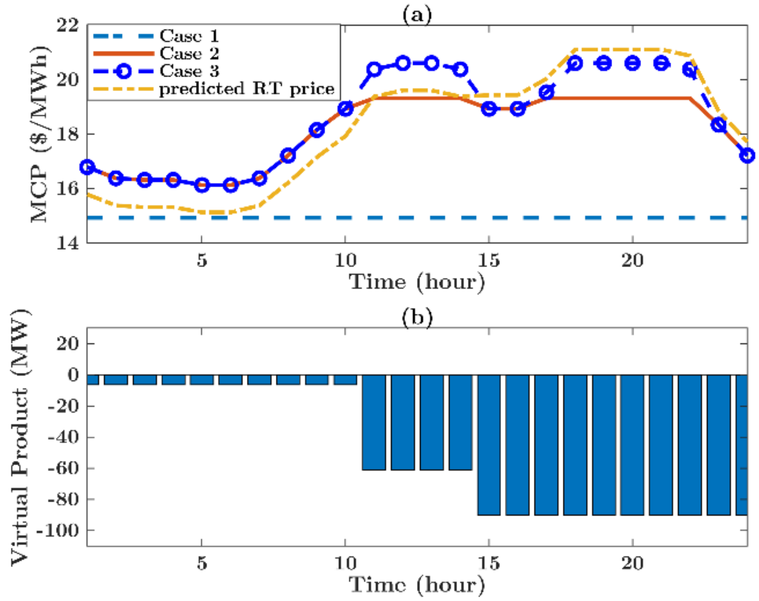


Figure 4.2 Effect of virtual transactions on market price in the IEEE 14-bus system. a) DA market prices for the three cases and the predicted RT price; b) Virtual transaction in Case 3.

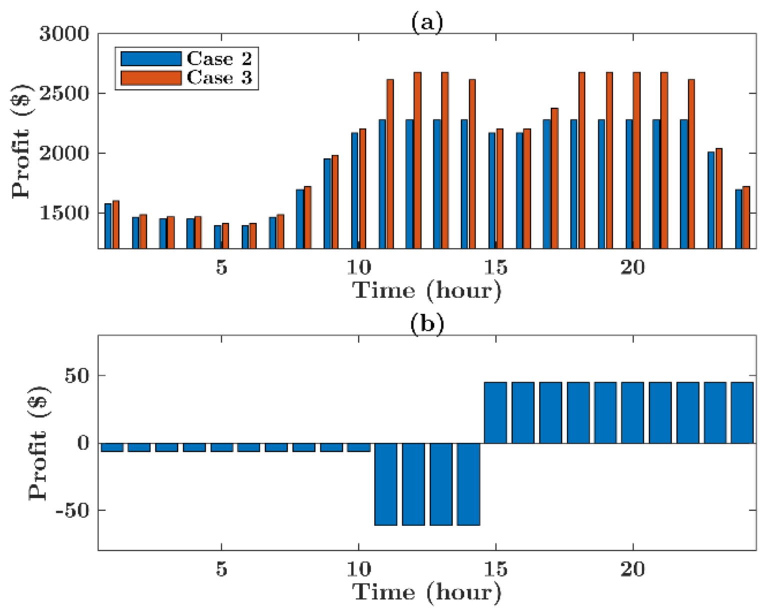


Figure 4.3 Profit comparison. a) Hourly physical generation profit for Case 2 and Case 3. b) Hourly virtual transaction profit in Case 3.

C) From hour 15 to hour 24, the predicted RT price is considerably higher than the DA price (as seen in Figure 4.2(a)), and strategic MP bids in a virtual demand which is expected to bring virtual transaction profit as long as the resulting DA price is maintained to be lower than the predicted RT price. In addition, the virtual demand increases the DA price and therefore brings higher physical generation profit.

For the above reasons, the strategic MP with virtual bidding capability (Case 3) achieves a higher total profit than Case 2, as shown in Figure 4.1 (b).

4.4.3. Results for Stochastic Condition. For the sake of illustration in this section, 15 scenarios are generated to model the other MPs' behaviors and RT market prices, however, the proposed method can be applied to a larger number of scenarios. In this section, it is assumed that the amount of power offered/bid by other MPs are known parameters by the strategic MP. Moreover, their unknown offer/bid prices are modeled by multiplying the marginal costs (Table 4.1) and bid prices (Table 4.3), respectively, with an uncertainty factor vector [1, 1.1, 1.3, 0.9, 0.75]. Therefore, five independent scenarios of rivals' strategies are designated, with the predefined probabilities of [0.7, 0.05, 0.1, 0.1, 0.05]. Moreover, to model the RT market price uncertainty, three scenarios (A, B and C) are generated by multiplying the RT market predicted prices (Table 4.4) with the uncertainty factor vector of [1, 1.25, 0.8]. The probabilities of these scenarios are assumed to be 0.8, 0.1, and 0.1, respectively. Due to the simplicity of illustration in this case study, transmission constraints were overlooked so that all buses have the same RT price. Considering the confidence level α to be 0.95, the single- level model ((4.31) – (4.45)) is solved for multiple value of β.

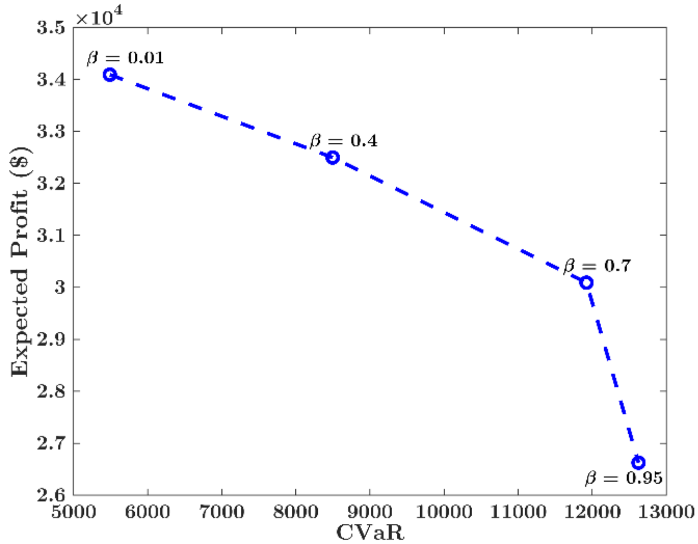


Figure 4.4 Efficient Frontier of Profit vs Risk for the IEEE 14-bus test system.

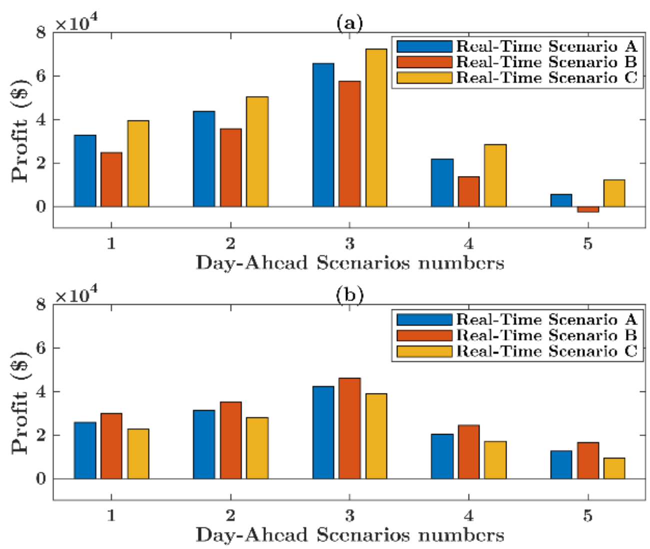


Figure 4.5 Profits of Risk-Taker MP versus Risk-Averse MP in different scenarios. a) risk-taker MP; b) risk-averse MP.

Figure 4.4 depicts the efficient frontier and indicates the reduction in the expected profit as the weighting factor β increases. It means that the strategic MP expects a higher profit when it takes the risk-taker position. However, it may experience money losses in certain situations, such as RT scenario B in conjunction with DA scenario 5, as shown in Figure 4.5(a). On the other hand, when the strategic MP adopts the risk-averse position, its expected profit declines, while its tailored optimal strategy assures positive profits in all situations, as illustrated in Figure 4.5(b). In other words, the strategic MP decreases its profit volatility and its expected profit.

4.4.4. Results for 39-bus System. To show the consistency of the results even for the bigger system with more buses, lines and MPs, the proposed model has been implemented for the 39-bus test system which data can be found in [89]. In this system, we select a strategic MP that owns 3 physical units and is able to bid virtual transactions in 4 different locations. The three generators are located at buses 34, 36 and 39 respectively, while the virtual transactions bid from buses 7, 12, 18 and 23 respectively. The same three cases (namely, Case 1, Case 2 and Case 3) defined in previous subsection are studied here. Figure 4.6 illustrates that, by applying the Deterministic Model, the strategic MP with the virtual bidding capability can gain more profit than the other two cases. Changes of market prices in the three cases are shown in Figure 4.7, which reinforces the observation from the previous section that the price influence of virtual transactions plays an important role in the profit maximization of the strategic MP.

To consider the uncertainty in other MPs' offers/bids and RT market prices, 7 different offer/bids of other MPs with a probability vector of [0.6 0.025 0.075 0.1 0.05 0.05 0.1] and 4 different scenarios of RT market price with a probability vector of [0.8 0.075 0.075 0.05] are taken into account to construct 28 scenarios in this case study.

The Stochastic model is solved for several values of β and $\alpha = 0.95$. The efficient frontier which displays the expected profits of the risk-taker and risk-averse strategic MP is depicted in Figure 4.8. Similar to the observations seen in the IEEE 14-bus test system, Figure 4.8 shows, as the risk aversion level increases, the strategic MP will have reduced profit and at the same time reduced profit volatility.

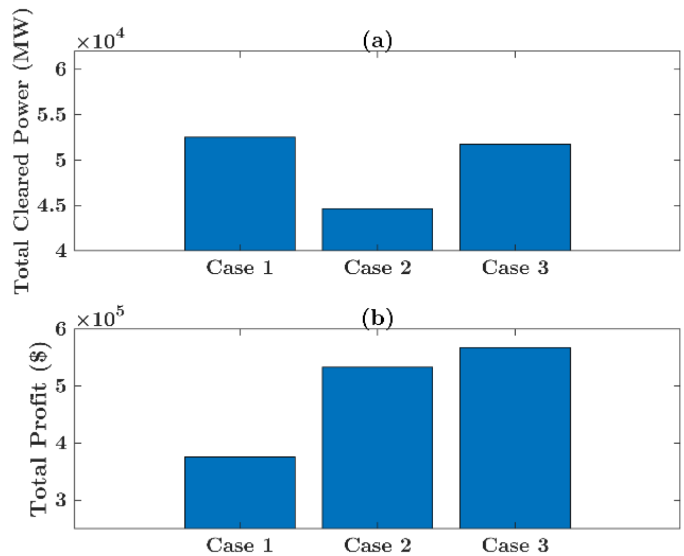


Figure 4.6 Results of the strategic MP in the IEEE 39-bus system. a) Total cleared power and b) Total profits of MP.

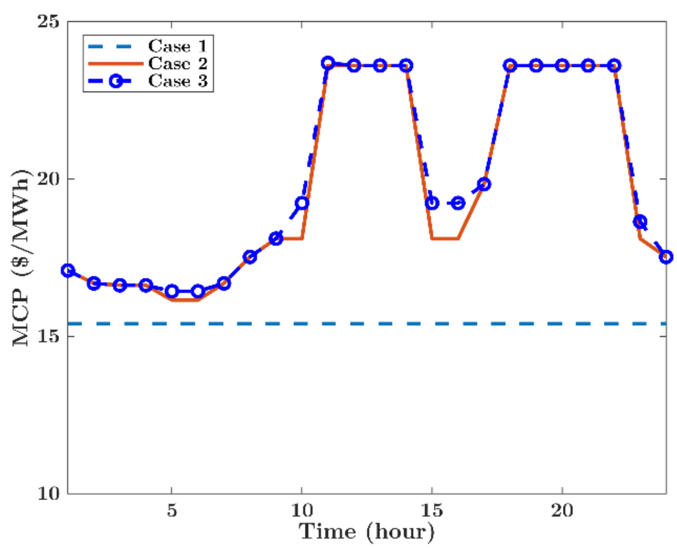


Figure 4.7 Market prices of the IEEE 39-bus system in different cases.

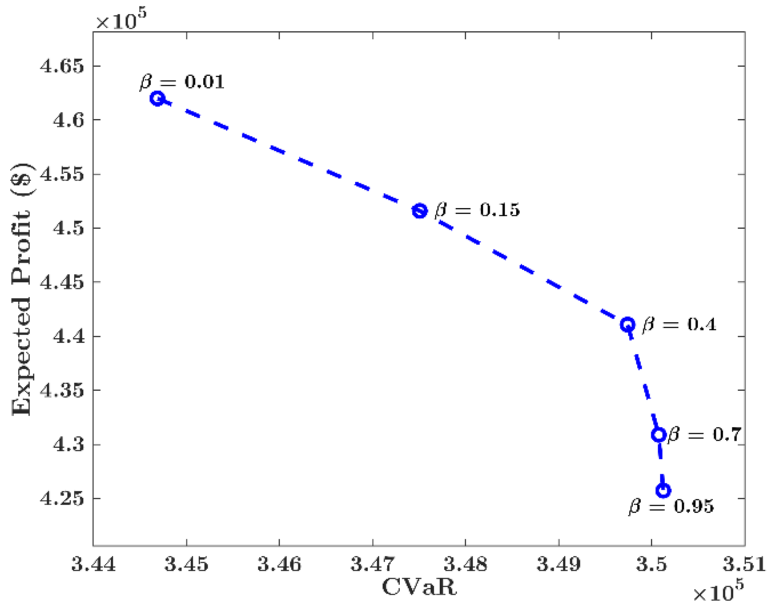


Figure 4.8 Efficient Frontier of Profit vs Risk for the IEEE 39-bus test system.

4.5. SECTION SUMMARY

The bidding strategy problem for physical market participants with virtual bidding capacity was covered in this section, along with the mathematical models for this rarely research yet practical problem. Then, to make the model closer to the practical application, uncertainties related to RT market prices, competitors' offers/bids in the DA market, and CVaR to quantify and regulate the financial risks related to the strategies, was included to the model. Bi-level optimization programming approach has been employed, in which LMPs are endogenous generated. Duality theorem, KKT conditions, SDT and Big-M method are employed to translate the bi-level problem into a MILP problem to be solved. The proposed model's capability to derive the strategic MP's optimal decisions is demonstrated by the simulation results. Employing the proposed models, the strategic MP can optimally determine the amount of physical/virtual transactions and manage its impact on the DA price, in order to achieve a balance between the physical generation profit and the virtual transaction profit. A case study on a deterministic model represents a few optimal strategies that utilize virtual transaction to influence DA price in a way that benefits the physical generation profit. Case studies for a stochastic model demonstrate the proposed method allows the strategic MP to choose a risk level which makes the compromise between the expected profit across all scenarios and the profit volatility in those scenarios.

5. BIDDING STRATEGY WITH JOINT PARTICIPATION IN FTR AUCTION AND DAY AHEAD MARKET CONSIDERING VIRTUAL BIDDING

5.1. BACKGROUND

After restructuring of the power industry, and holding different electricity markets with imperfect competition, MPs may experience different prices at different locations of the system, which is called locational marginal price (LMP). In this situation, MPs may be exposed to high and unpredictable congestion charges since the payment to the generators may differ from the payment collected from consumers. ISOs hold an independent auction known as a Financial Transmission Right (FTR) auction in which the FTRs values are determined based on the DA LMP differences between the beginning nodes (source) and the end nodes (sink) of the FTRs paths. This process protects the MPs from the uncertainty of the congestion price and provides a fair approach to allocating the leftover funds. This financial instrument gives the MP the chance to hedge risk while also creating the potential of manipulating the wholesale market pricing in order to optimize its profit profile. The crucial issue is how a strategic MP should build its offering strategy in both the wholesale market and the FTR auction, which is addressed in this section.

Virtual bids, which have been discussed in previous sections, are useful tools for filling in the gaps between LMPs in the DA and RT markets. Moreover, it can be employed by MPs as a tool to develop the most profitable strategies. This section therefore suggests a two-stage bi-level optimization model for creating a joint offering strategy for a strategic GenCo that takes part in both the FTR auction and the DA market and has the ability to submit virtual bids in the DA market. The upper-level (UL) of the first stage problem models the strategic GenCo's profit maximization problem in the FTR auction, and the lower-level represents the FTR auction clearing process that provides the FTR cost price for the UL model. Moreover, as the revenue of the GenCo in FTR auction is dependent on the LMP difference between the sink and source buses in the DA market, this LMP difference are transferred from the second stage problem which models the DA market. Additionally, the second stage problem, in which the upper-level (UL) subproblem mimics the GenCo's profit maximization problem, simulates the strategic decision-making process of this MP in the DA market. The only relation between the first stage and second stage problems is the DA LMP, which appears in the first stage objective function, meaning that this problem can be written as a single stage bi-level problem. Finally, this problem is converted into a single-stage, single-level equivalent problem using KKT optimality conditions and strong duality theory (SDT). Case studies are provided to show the effectiveness of the proposed model.

5.2. MANIPULATION OF FTR VALUE BY VIRTUAL BIDDING

According to the PJM report [25], virtual bids that can be submitted into the market in form of either DEC or INC. These products are clearly able to change the market prices. The amount of power that is purchased (or sold) by the virtual bidder in the DA market is exactly compensated by a sale (or purchase) of the same amount of power in the RT market. As a result, the net amount of power that is traded in these markets is zero, which is one of the distinguishing characteristics of the virtual bid. The difference between the DA/RT LMP and the cleared virtual power is used to calculate the virtual bidder's profit. Simply put, the DA/RT LMP discrepancies are used to evaluate the value of a virtual bid. Here, the modified version of the five-bus test system described in

[90] is used to demonstrate this point. There are 5 generators, 3 loads, 6 transmission lines in this system. All offer (bid) quantities and generators' (loads') prices, and the transmission line capacities are depicted in Figure 5.1 beside each element. Assume that a virtual bidder intends to submit VB amount of DECs at bus B. Considering the fixed forecasted RT LMP, the value of the virtual bid ($\lambda^{RT} - \lambda^{DA}$) decreases because the DA LMP increases, when the amount of DECs increases at this bus (Figure 5.2). The greater the cleared DEC amount, the greater the potential profit for the virtual bidder. But as cleared DEC amounts rise, the price differential between RT LMP and DA LMP reduces, decreasing the virtual bidder's profit. As is seen in Figure 5.2, the virtual bidder can maximize the profit ($294.64) by placing 9MW DECs at bus B. In contrast, the FTR gives MPs a way to protect themselves from the risk of congestion, and its value is equivalent to the difference in LMP between sink and source buses. For example, if an MP owns F MW FTR from bus "E" ($source$) to bus "B" ($sink$), its revenue would be equal to $(\lambda_E^{DA} - \lambda_B^{DA}) \times F$. As this instrument's value is calculated based on the DA LMP, there is an opportunity for an FTR holder to manipulate the DA LMP, thus maximizing its total profit. Moreover, an MP can change the DA LMP without the obligation of generating or consuming any physical power. Therefore, placing virtual bids at specific buses in the system can worsen the line congestion in the DA market and increase the DA LMP difference between the sink and source buses, then it provides more FTR profit for the MP. To illustrate this point, the previous example is extended by assuming that the MP holds an FTR from bus "E" to bus "B". As is shown in Figure 5.3, DA LMP at bus "B" increases when the more DEC is cleared at this bus; therefore, the FTR value ($\lambda_E^{DA} - \lambda_B^{DA}$) increases, and MP makes more FTR profit.

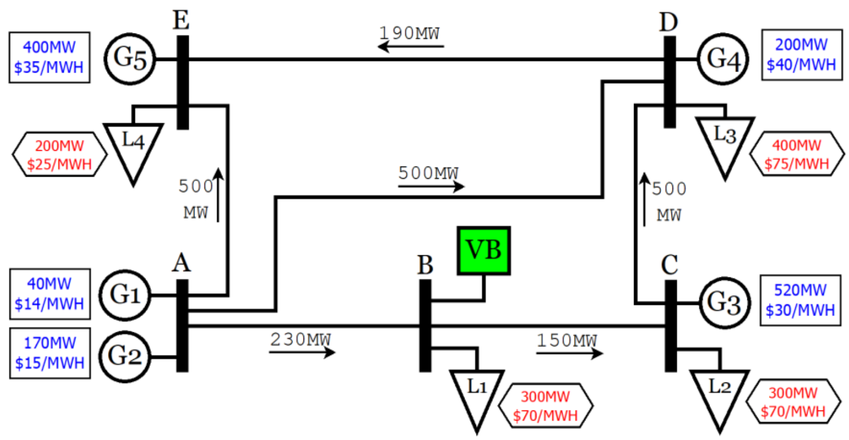


Figure 5.1 Five-bus test system.

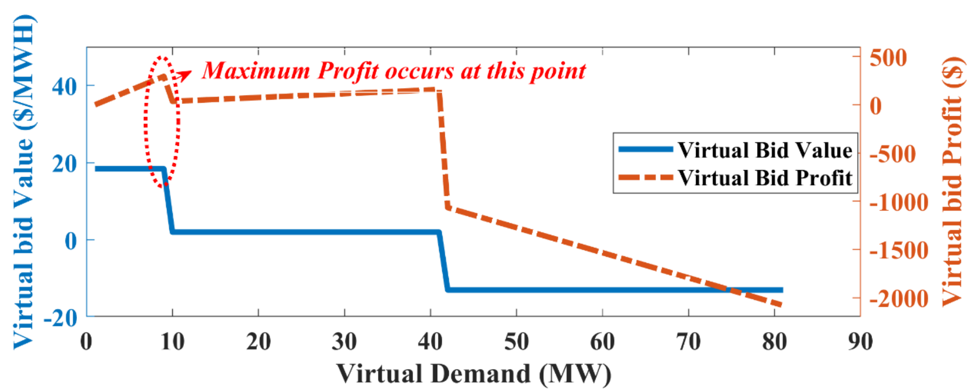


Figure 5.2 Virtual demand value and virtual profit of trader in 5-bus system.

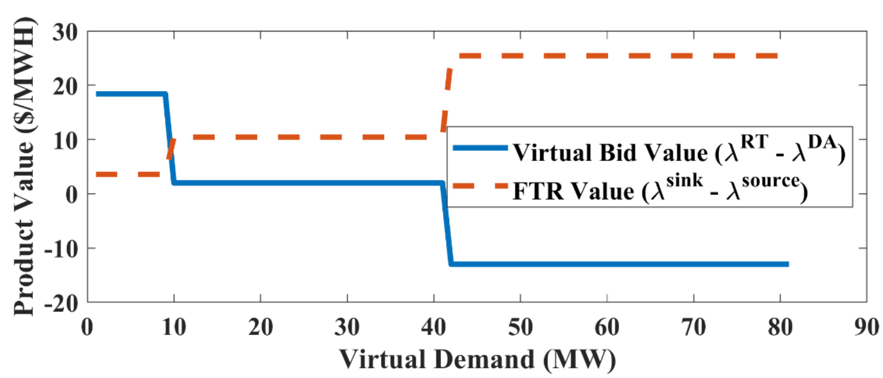


Figure 5.3 Virtual demand value and FTR value profiles by placing DECs at bus “B” of 5-bus system.

The total profit made from both the FTR and the virtual transactions is shown in Figure 5.4. According to the data shown, the highest possible value of total profit is \$994.4, and this occurs when 41MW of virtual demand is cleared in the DA market. Even if the MP incurs a slight financial loss in the DA market as a result of submitting an increased quantity of virtual demand, the MP's overall profit is optimized by generating an increased amount of FTR profit. To put it another way, the capability of the MP to raise the value of FTR provides an incentive for him or her to position additional DECs at the sink bus in order to maximize the overall payoff.

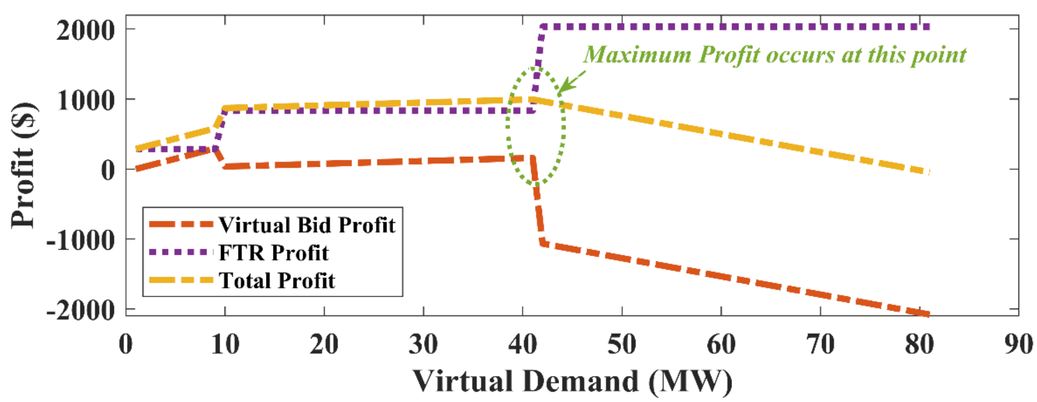


Figure 5.4 Virtual profit, FTR profit and total profit profiles of MP by placing DECs at bus “B” of 5-bus system.

5.3. PROPOSED OFFERING STRATEGY MODEL

FTRs provide MPs a helpful means of protecting themselves from the price uncertainty caused by congestions in the market. The DA LMP that is resolved in the DA market is used to calculate payments to FTR holders. The DA LMP differential that exists between an FTR's source buses and sink buses is determined by the offering strategies of the MPs as well as the settlement of the DA market. As a result, the methods for the MP's offering strategy design in the FTR auction and the DA market are highly associated with one another and need to be investigated together. As a consequence of this, participants in the FTR and DA markets may choose to devise strategies for their bids that aim to maximize the total payoffs they get from both markets. This study attempts to design a paradigm for a price-maker MP whose offer can alter the DA market prices. A strategic MP needs a DA market model to observe the market's reaction to the imposed strategies, instead of predicting the DA LMPs. Furthermore, an FTR auction model is needed to derive the market price in the FTR auction, which is required to calculate the FTR cost [91]. As a result, in this section, a two-stage bi-level optimization model is proposed to capture the strategic MP's offering strategy in FTR auction and DA market.

Figure 5.5 represents the time sequence of power markets. As a part of forward markets, monthly FTR auction is held a month prior to the DA market [71], and an MP requires the forecasted DA LMP to design its FTR offering strategy. This study aims to design a bidding strategy for a price-maker MP participating in both monthly FTR auction and DA market.

Figure 5.5 Time sequence of different electricity markets.

Figure 5.6 presents the decision graph of the proposed model. As shown, the total profit of the strategic MP comprises the FTR profit and the profit from the physical generation and virtual bids in the DA markets. Interdependency of these two markets, from the MP’s viewpoint, comes from the DA LMP of the sink and source buses, which are determined after the DA market clearing process and are required to compute the revenue of MP from its FTR position

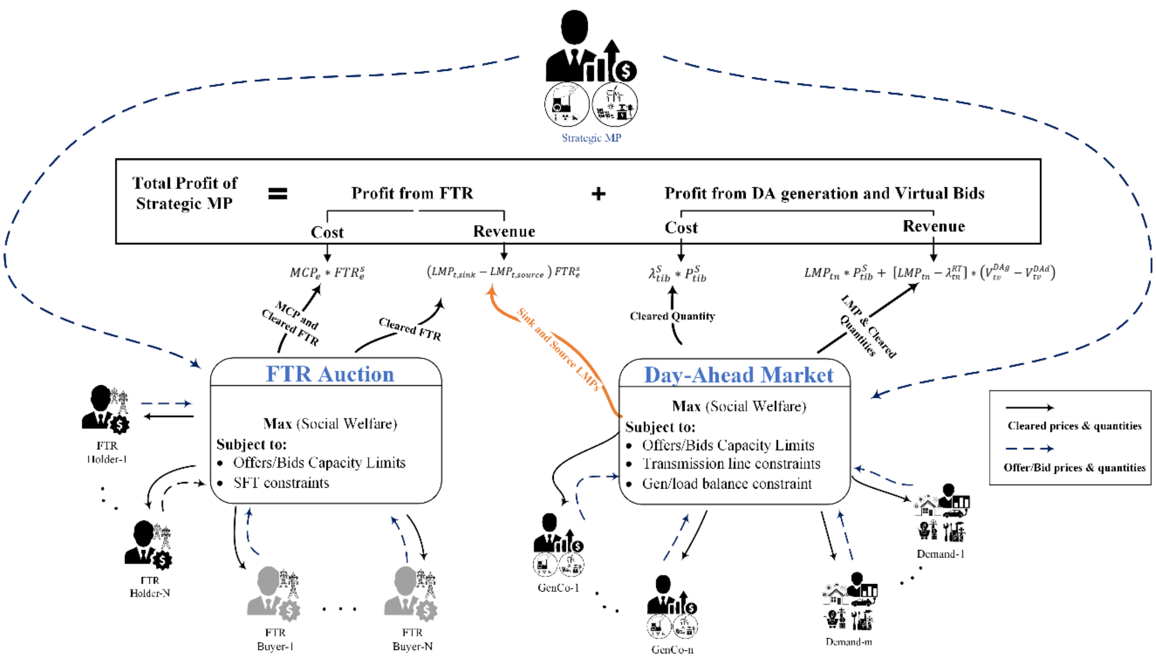


Figure 5.6 Offering Strategy of strategic MP in both FTR and DA markets.

A strategic market participant may utilize a DA market model in order to examine how the market responds to the tactics that are imposed on it. In addition, an FTR auction model is necessary in order to extract the market price in the FTR auction, which is necessary in order to quantify the cost of the FTR. As a consequence of this, a two-stage bi-level optimization model is proposed in this work in order to capture the strategic MP's strategy in both the FTR auction and the DA market. The first stage problem is a bi-level optimization model, as can be shown in Figure 5.7. This model represents the FTR auction clearing process in the LL subproblem, and it maximizes the profit that the MP makes from the FTR auction in the UL subproblem. The DA LMPs that are necessary for the calculation of the FTR revenue originate from the second stage at this point. In the second stage, a second bi-level optimization problem is constructed. This problem represents the maximizing problem at the upper level (UL), while the DA cleaning method is modeled at the lower level (LL).

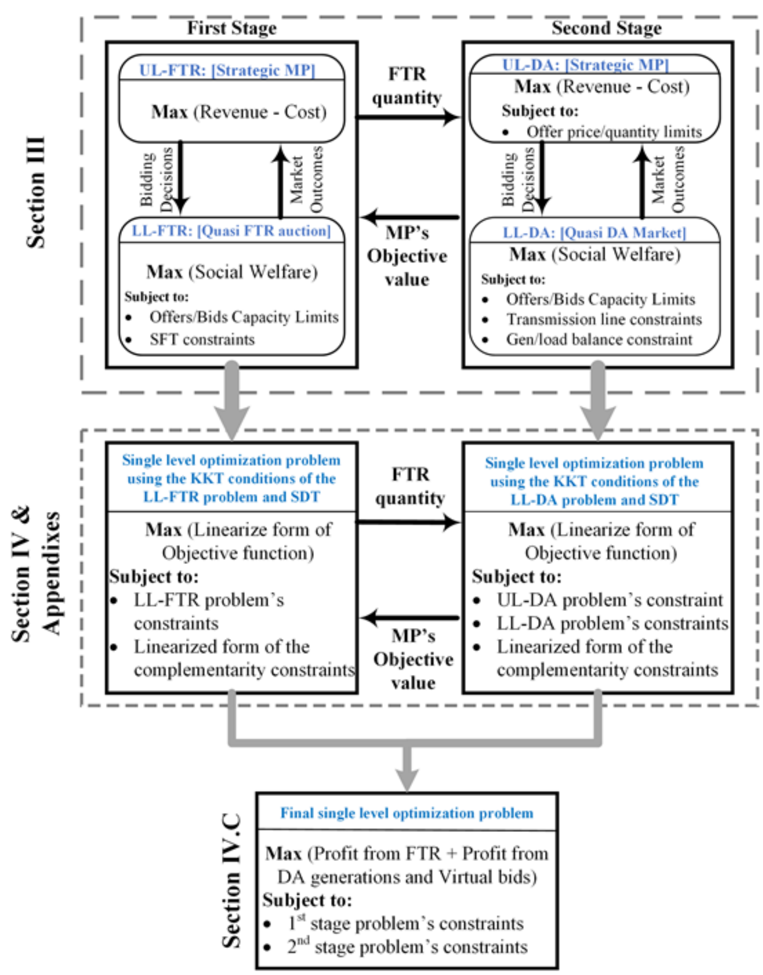


Figure 5.7 Proposed two-stage bi-level optimization model and the solution methodology.

5.4. MATHEMATICAL FORMULATION

In order to make it easier to explain how the model is formed, each of the stages is modeled on its own first. After that, the necessary information that is sent back and forth between the stages is stated, and then the whole model is provided. Therefore, the first stage bi-level model, which represents the offering strategy model in FTR auction, is described at the first step, and after that, the second stage bi-level model is discussed. Lastly, the model is constructed using the data that was exchanged between these stages.

5.4.1. First Stage: Offering Strategy Model in FTR Auction. The first stage of the proposed model tries to maximize the MP's profit participating in the FTR auction. To consider the influence of MP's bids on the FTR auction price, bi-level optimization model is formed as follows:

A) Upper-Level

$$\underset{\Omega_1^{FTR}}{\text{Min.}} \sum_{t} \left(MCP_e FTR_e^s - \left(LMP_{t,sink} - LMP_{t,source} \right) FTR_e^s \right) \tag{5.1}$$

Subject to:

$$0 \leq FTR_e^{Sbid} \leq \overline{FTR}_e^S \tag{5.2}$$

$$\rho_e^s \geq 0 \tag{5.3}$$

B) Lower-Level

$FTR_e^s, MCP_e \in \arg \{$

$$\underset{\Omega_2^{FTR}}{\text{Min.}} \sum_{c \in N_{sell}} \sigma_c FTR_c - \sum_{e} \rho_e^s FTR_e^s - \sum_{f \in \{N_{pur} - e\}} \rho_f FTR_f \tag{5.4}$$

Subject to:

$$0 \leq FTR_e^s \leq FTR_e^{Sbid} : \underline{\tau}_e^S, \overline{\tau}_e^S, \ \forall e \tag{5.5}$$

$$0 \leq FTR_f \leq \overline{FTR}_f \ : \ \underline{\tau}_f \, , \overline{\tau}_f , \forall f \in \{N_{pur} - e\} \tag{5.6}$$

$$0 \leq FTR_c \leq \overline{FTR}_c : \ \underline{\tau}_c \, , \overline{\tau}_c , \forall c \in N_{sell} \tag{5.7}$$

$$-\overline{F}_l \leq LF_l^{ex} + LF_l \leq \overline{F}_l \ : \ \underline{\xi}_l \, , \overline{\xi}_l \quad \forall l \tag{5.8}$$

$$LF_l = \sum_m H_{lm} \, FTR_m \, , \forall l, m \in \{N_{sell}, N_{pur}\} \tag{5.9}$$

$$MCP_m = \sum_l H_{lm} (\, \overline{\xi}_l - \underline{\xi}_l) \, , \forall m \in \{N_{sell}, N_{pur}\} \tag{5.10}$$

$$H_{lm} = \ PTDF_{l,source} - \ PTDF_{l,sink} \tag{5.11}$$

The objective of the MP is to minimize the negative of profit in FTR auction using (5.1) that models the FTR cost in the first term ($MCP_e FTR_e^s$) and FTR revenue in the second term (($LMP_{t,sink} - LMP_{t,source}$) FTR_e^s). FTR unit price (MCP_e) comes from the FTR auction clearing procedure that is modeled at the LL subproblem ((5.4) – (5.11)). Additionally, FTR revenue requires the second stage information to be calculated. In this model $\Omega_1^{FTR} = \left\{FTR_e^{Sbid}, \rho_e^s \right\}$ is the MP's set of decision variables in the UL subproblem. FTR bid quantity is bounded by (5.2) and (5.3), forcing the FTR bid price to be positive. FTR auction model seeks to minimize the minus social welfare regarding the simultaneous feasibility test (SFT) constraints. LL decision variables are represented by $\Omega_2^{FTR} = \left\{FTR_e^s, \ FTR_f, FTR_c\right\}$. Cleared FTR quantities are bound by their maximum and minimum FTR bids or offers in (5.5) – (5.7). Constraint (5.8) limits the line flows calculated by (5.9) to the transmission line capacities. LF_l^{ex} in (5.8) denotes the line flows caused by the existing FTRs contracted in the secondary market [92, 93]. Employing the Lagrangian coefficients of (5.8), FTR auction price can be determined by (5.10). Note that shift factor versus FTR bids/offers (H_{lm}) is required to calculate the line flows and

FTR auction price in this model. This parameter can be obtained by subtracting the PTDF of the line l vs. the $source$ from that of the $sink$ buses (5.11). The FTR auctioneer takes ρ_e^s as a parameter, meaning the LL subproblem is linear and convex, thus, it is replaced by KKT conditions. Therefore, the *Model (1)* is written as a single level optimization problem known as MPEC which is detailed in APPENDIX (PART A1).

5.4.2. Second Stage: Offering Strategy Model in DA Market. As explained, FTR revenue is calculated using the DA LMPs at $sink$ and $source$ buses. It is assumed that the MP is a price-maker player in the DA market, thus it is needed to model the MP's offering strategy decision-making problem in the DA market and study the effects of its offers (quantity and price) on the DA market clearing outcomes. Furthermore, the strategic MP submits the virtual bids from different locations in the DA market, which empowers the MP to change the DA LMPs for its own interest. Therefore, the second stage of the proposed model represents the offering strategy problem of the MP and aims to maximize the MP's payoff in the DA market as follows:

A) Upper-Level

$$\underset{\Omega_1^{DA}}{\text{Min.}} \sum_{t(i\in\psi_n)b} [\lambda_{tib}^S - LMP_{tn}]\, P_{tib}^S - \sum_{t(v\in\psi_n)} [LMP_{tn} - \lambda_{tn}^{RT}]\left(V_{tv}^{DAg} - V_{tv}^{DAd}\right) \tag{5.12}$$

Subject to:

$$\sum_b P_{(t+1)ib}^s - \sum_b P_{tib}^s \le R_i^{UP}, \quad \forall t, i \tag{5.13}$$

$$\sum_b P_{tib}^s - \sum_b P_{(t+1)ib}^s \le R_i^{LO}, \quad \forall t, i \tag{5.14}$$

$$0 \le P_{tib}^{Sbid} \le \overline{P}_{tib}^{S}, \quad \forall t, i, b \tag{5.15}$$

$$0 \le V_{tv}^{bidG} \le V_{tv}^{budget} Ug_{tv}\,, \quad \forall t, v \tag{5.16}$$

$$0 \le V_{tv}^{bidD} \le V_{tv}^{budget} Ud_{tv}, \quad \forall t, v \tag{5.17}$$

$$Ug_{tv} + Ud_{tv} \le 1, \quad \forall t, v \tag{5.18}$$

$$\alpha_{tib}^{S} \ge 0, \alpha_{tv}^{bidG} \ge 0, \alpha_{tv}^{bidD} \ge 0 \tag{5.19}$$

B) Lower-Level

$$P_{tib}^{S}, V_{tv}^{bidG}, V_{tv}^{bidD} \in \arg \{$$

$$\begin{aligned} \underset{\Omega_2^{DA}}{\text{Min.}} \sum_{tib} \alpha_{tib}^{S} P_{tib}^{S} + \sum_{tjb} \lambda_{tjb}^{g} P_{tjb}^{g} - \sum_{tdk} \lambda_{tdk}^{d} P_{tdk}^{d} \\ + \sum_{tv} (\alpha_{tv}^{bidG} V_{tv}^{DAg} - \alpha_{tv}^{bidD} V_{tv}^{DAd}) \end{aligned} \tag{5.20}$$

Subject to:

$$\begin{aligned} \sum_{v \in \psi_n} (V_{tv}^{DAg} - V_{tv}^{DAd}) + \sum_{(i \in \psi_n)b} P_{tib}^{S} + \sum_{(j \in \psi_n)b} P_{tjb}^{g} - \sum_{(d \in \psi_n)k} P_{tdk}^{d} = inj_{tn} \\ : \; LMP_{tn}, \quad \forall t, n \end{aligned} \tag{5.21}$$

$$0 \le P_{tib}^{s} \le P_{tib}^{Sbid} \;\; : \; \underline{\mu}_{tib}^{S}, \overline{\mu}_{tib}^{S}, \;\; \forall t, i, b \tag{5.22}$$

$$0 \le P_{tjb}^{g} \le \overline{P}_{tjb}^{G} \;\; : \; \underline{\mu}_{tjb}^{G}, \overline{\mu}_{tjb}^{G}, \;\; \forall t, j, b \tag{5.23}$$

$$0 \le P_{tdk}^{d} \le \overline{P}_{tdk}^{D} \; : \; \underline{\mu}_{tdk}^{D}, \overline{\mu}_{tdk}^{D}, \;\; \forall t, d, k \tag{5.24}$$

$$0 \le V_{tv}^{DAg} \le V_{tv}^{bidG} \; : \; \underline{\mu}_{tv}^{Vg}, \bar{\mu}_{tv}^{Vg} \;\; , \;\; \forall t, v \tag{5.25}$$

$$0 \le V_{tv}^{DAd} \le V_{tv}^{bidD} \; : \underline{\mu}_{tv}^{Vd}, \bar{\mu}_{tv}^{Vd} \;\; , \;\; \forall t, v \tag{5.26}$$

$$-\underline{F_l} \le F_{tl} \le \overline{F}_l \; : \; \underline{\vartheta}_{tl}, \overline{\vartheta}_{tl} \quad \forall t, l \tag{5.27}$$

$$\sum_{n} inj_{tn} = 0 \quad , \quad \forall t \tag{5.28}$$

$$F_{tl} = \sum_{n} PTDF_{nl}\, inj_{tn} \quad \forall t, \forall l \quad \}. \tag{5.29}$$

The objective function (5.12) consists of two terms that represent the negative of MP's profits, as obtained by physical power generation and virtual bid, respectively. Ramp-up and ramp-down constraints of physical generations are represented by (5.13) and (5.14). Constraints (5.15) – (5.17) denote the maximum and minimum physical power offers and virtual bids, respectively. Constraint (5.18) declares that the virtual bids cannot be simultaneously generation and demand at each time period. Nonnegativity constraints of offers/bids prices are illustrated by (5.19). The set of UL decision variables is $\Omega_1^{DA} = \{P_{tib}^{Sbid}, \alpha_{tib}^{S}, V_{tv}^{bidG}, \alpha_{tv}^{bidG}, V_{tv}^{bidD}, \alpha_{tv}^{bidD}, Ug_{tv}, Ud_{tv}\}$. The objective of the LL subproblem that represents the DA market clearing model is to minimize the negative of social welfare. The first two terms of the objective function (5.20) represent the physical generations offers of the strategic and nonstrategic MPs, respectively. The third term models the physical loads bids and the fourth term denotes the virtual generations and demands bids. Generation-load balance constraint is represented by (5.21). Constraints (5.22) – (5.26) limit the strategic MP's generation power, nonstrategic MP's generation power, loads power, virtual generation, and virtual demand quantities to their corresponding maximum and minimum offers or bids. Power flows of transmission lines, which are calculated by (5.29), are bounded by their maximum capacities. The LL decision variable set is stated as $\Omega_2^{DA} = \{P_{tib}^{S}, P_{tjb}^{g}, P_{tdk}^{d}, V_{tv}^{DAg}, V_{tv}^{DAd}\}$. ISO takes the offer price of physical generation along with the bid prices of virtual transactions as parameters, thus the LL subproblem is linear and convex. Employing the methodology introduced in the previous subsection, the single level optimization model of the second stage problem is constructed as expressed in APPENDIX (PART A2).

It is worth mentioning that the nonlinear terms in the objective functions (5.1) and (5.12) are linearized using the SDT approach [54]. Moreover, complementarity nonlinear constraints can be linearized using Big M method described in Section 4.

Note that although the MP's offering strategy model in FTR auction depends on the DA market outcomes, the actual DA market model is independent of the FTR auction model and no FTR market outcomes is needed to create the offering strategy model in DA market. To solve this issue, the second term of the objective function (5.1) is transferred to the second stage objective function (5.12). This way, the required transition information from the first stage problem to the second stage problem will be FTR_e^s, and the objective value of the second stage will be the required data passed from the second stage problem to the first stage problem. This is noticeably depicted in Figure 5.7.

5.4.3. Proposed Two-Stage Bi-Level Optimization Model. Employing the bi-level optimization models for both stages and the necessary transition data between these stages, the final model is developed as follows:

$$\begin{aligned} \underset{\Delta}{\text{Minimize}} \sum_{t} \Bigg(& -\sum_{f} \rho_f FTR_f + \sum_{f} \sigma_c FTR_c + \sum_{f} \overline{\tau}_f \overline{FTR_f} + \sum_{c} \overline{\tau}_c \overline{FTR_c} \\ & + \sum_{tl} \left(\overline{\xi}_l + \underline{\xi}_l \right) \overline{F}_l - \left(LMP_{t,sink} - LMP_{t,source} \right) FTR_e^s \Bigg) \\ & + \Bigg[\sum_{tib} \Bigg(\lambda_{tib}^S P_{tib}^s + \sum_{t(v \in \psi_n)} \lambda_{tn}^{RT} \left(V_{tv}^{DAg} - V_{tv}^{DAd} \right) \Bigg) \\ & + \Bigg(\sum_{tjb} \lambda_{tjb}^g P_{tjb}^g + \sum_{tjb} \overline{\mu}_{tjb}^G \overline{P}_{tjb}^G - \sum_{tdk} \lambda_{tdk}^d P_{tdk}^d + \sum_{tdk} \overline{\mu}_{tdk}^D \overline{P}_{tdk}^D \\ & + \sum_{tl} \left(\underline{\vartheta}_{tl} + \overline{\vartheta}_{tl} \right) \overline{F}_l \Bigg) \Bigg] \end{aligned} \tag{5.30}$$

Constraints (A3.2), (A3.3), (A3.5), (A3.6) (5.31) where the decision variable set is $\Delta = \{\Omega_1^{FTR}, \Omega_2^{FTR}, \Omega_1^{DA}, \Omega_2^{DA}, \text{all dual variables}\}$. Equation (5.31) represents the first and second stages' constraints, which are described in APPENDIX (PART A3).

5.5. ILLUSTRATIVE EXAMPLE

To illustrate the mechanism and the functionality of the proposed model, an illustrative example is designed for this section, and it is implemented on 5-bus test system which is described in Section 4.

5.5.1. Data and Setups. The data of other MPs in both the FTR auction and the DA market are necessary in order to assist the strategic MP in making joint offering strategy. Figure 5.8 illustrates the sink and source buses of the offers and bids made by all participants. It is generally accepted that Strategic MP will participate in the FTR auction. In here, it is assumed that the MP will play in a FTR auction as a buyer, and it tries to buy FTR from buses 2 through 5. (FTR_5 in Figure 5.8). In Table 5.1, which depicts the FTR number, source and sink buses, players status, bid prices, and quantities in separate columns, A summary of the information on the offers and bids that were made by seven different players during the FTR auction, can be found.

Offers/bids of all physical generators/loads in DA market are depicted in Figure 5.9 beside their corresponding elements. Moreover, the transmission lines capacities are displayed on corresponding lines. It is assumed that the strategic MP owns a generator 5 (G_5) located at bus "E" with the marginal cost equal to \$35/MWH.

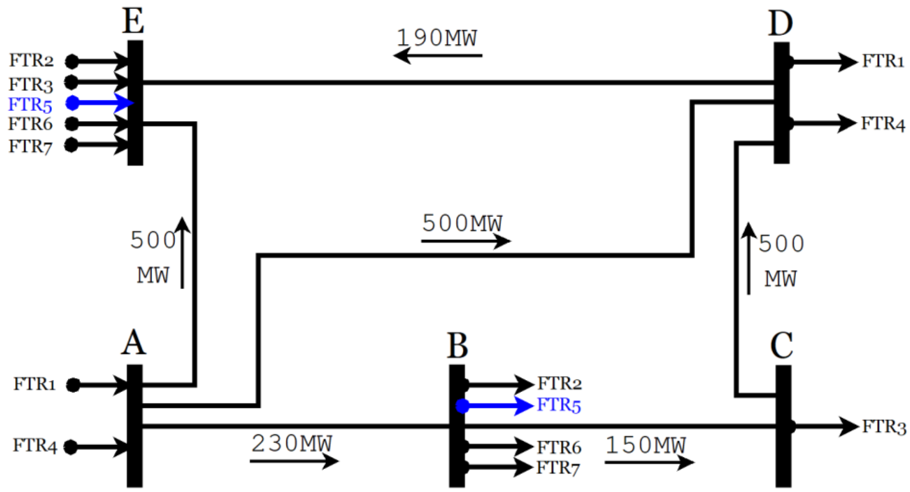


Figure 5.8 FTR offers and bids illustration in 5-bus test system.

Table 5.1 FTR offers/bids of all MPs in the FTR Auction.

FTR #	Source (bus #)	Sink (bus #)	Status (Buyer/Seller)	Bid Price ($/MWH)	Bid Quantity (MW)
1	1	4	Seller	5	75
2	5	2	Buyer	8	140
3	5	3	Seller	6	120
4	1	4	Buyer	9	110
5	5	2	Buyer	*Variable*	*Variable*
6	5	2	Buyer	8	100
7	5	2	Buyer	10	100

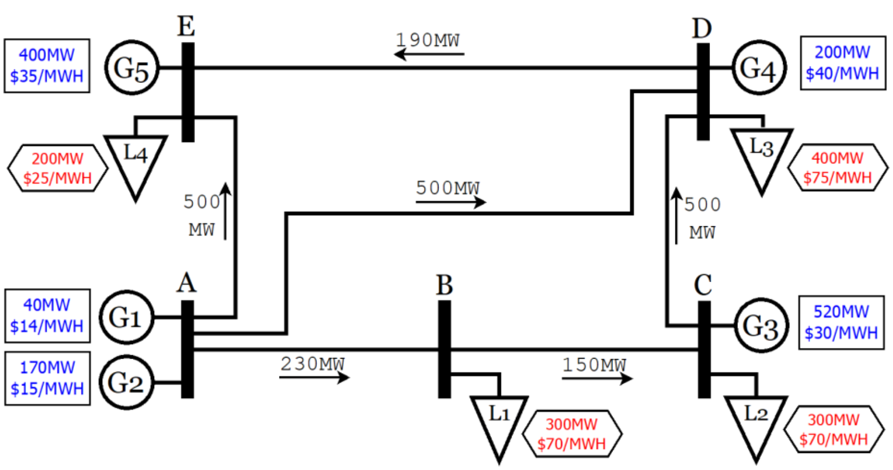


Figure 5.9 Offers/bids of all physical generators/loads in DA market.

To present the effectiveness of the proposed model, four different cases are designed as follows:

- Case 1: the strategic MP bids separately in FTR auction and DA market with the assumption that the accurate prediction of DA LMP difference between source and sink buses (DLMP) is available. In this case, Model (A3) [described in APPENDIX (PART A3)] are solved separately to determine the offering strategies of the MP in FTR auction and DA market.
- Case 2: this case is similar to Case 1, except that the accurate DLMP forecast is not available.
- Case 3: in Case 1 and Case 2, the strategic MP's offering decisions in FTR auction are not included in the MP's decision-making process in DA market, which is considered in this case. Therefore, Model (A3.1 – A3.3) is solved at the first step, similar to Case 2, and then the cleared FTR quantity and FTR auction price are passed to the modified version of Model (A3.4 – A3.6) that includes the first stage results in its objective function to capture the offering decision of MP for the DA market.
- Case 4: applies the proposed joint offering strategy decision making model (Model (5.30) – (5.31)) that simultaneously optimize the decisions of the MP in FTR auction and DA market.

Note that to emphasize the influence of the virtual bids on the final decisions and profit of the strategic MP, these designed cases are solved twice, with and without considering the virtual bids, and the results are compared afterwards.

5.5.2. Results and Discussion. Strategic MP's FTR auction profit, DA market profit, and total profit are illustrated in Figure 5.10. Employing inaccurate DA LMP predictions in Case 2 and Case 3 causes negative profits in FTR auction for these cases. However, including the FTR offering decisions in the second stage of Case 3, makes the MP offer its power with higher price ($53.3/MWH) in the DA market, so the DA LMP at bus 2 will be $70/MWH because of the congestion at line BC. This causes the value of FTR to change from [(55.017 – 44.57) – 30.3 = $(-19.85)/MWH] in Case 2 to [(70 – 53.3) – 30.3 = $(-13.6)/MWH] in Case 3; therefore, MP loses less money from the FTR auction (Table 5.2). Although this action caused lower profit in the DA market because of the MP's lower cleared power (133.18MW) in Case 3 in comparison with that of Case 2 (270.45 MW), the total profit in Case 3 is higher than in Case 2.

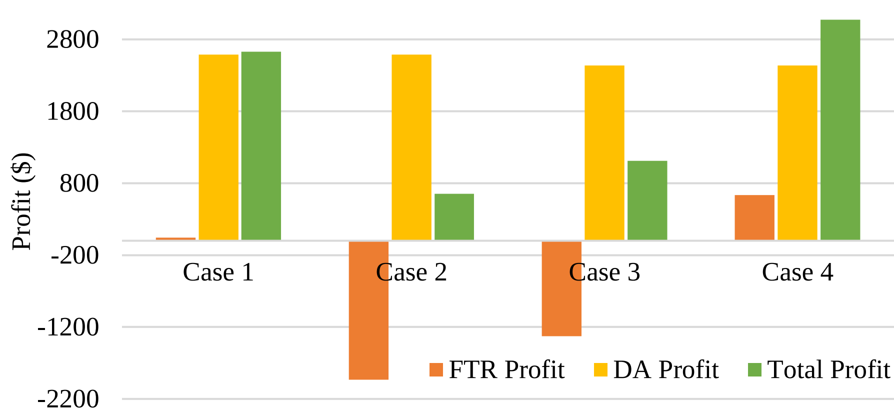


Figure 5.10 MP's FTR profit, DA profit, and Total profit in different cases.

Comparison between Case 1 and Case 4 declares that although the offering decisions of MP in FTR auction in both cases are the same (Table 5.2), MP differs its strategy in the DA market (offers its power with higher price) to increase the FTR value from [(55.017 – 44.57) – 10 = $0.45/MWH] in Case 1 to [(70 – 53.3) – 10 = $6.7/MWH] in Case 4, thereby making more profit in the FTR auction. This way, MP loses a small amount of money in the DA market, however, this change in the DA profit is smaller than the MP's FTR auction profit. Put simply, the strategic MP intentionally loses money in the DA market (by its strategic decisions) to increase the FTR value and maximize its total profit. To present the effect of virtual bids on MP's offering strategy decision making, it is assumed that the strategic MP is able to submit the maximum virtual bids (generation/load) of 200MW in buses 2 and 5. Real-time prices are predicted to be $30/MWH for all buses. Table 5.3 summarizes the results of different cases implementation considering the virtual bids. Comparing the results of Case 2 and Case 3 in this test with the results of the same cases without considering the virtual bids, shows that the MP can make more total profits in both cases. This happens because MP prefers to employ virtual generation at bus 5 instead of submitting the expensive physical generation to alter the DA LMPs. According to Figure 5.11, virtual bids provide the ability to make the strategic MP increase the FTR value and also make more profit from virtual bidding in DA market, which results in a higher total profit in Case 4 compared to Case 1. To be more specific, it can be said that the MP prefers to submit the lower virtual generation (77.56MW) at bus 2 with the higher price ($70/MWH) in Case 4 instead of selling 200MW at bus 5 with the lower price ($44.57) in Case 1. This way MP makes more profit from virtual bidding, and at the same time, the FTR value raises to $6.7/MWH. To further specify the advantages of employing virtual bids, the results of Case 4 without virtual bids (Table 5.2) were compared to the results of Case 4 when the MP employs virtual bids (Table 5.2).

Table 5.2 Results of Cases for Illustrative Example Without Considering Virtual Bids.

	offering status (Separately/Jointly)	FTR Offer Price ($/MWH)	FTR Cleared Power (MW)	FTR auction Price ($/MWH)	DA Offer Price ($/MWH)	DA Cleared Power (MW)	DA LMP@ Bus 5 ($/MWH)	DA LMP@ Bus 2 ($/MWH)	FTR Profit ($)	DA Profit ($)	Total Profit ($)
Case 1	Separately	10	94.99	10	44.57	270.45	44.57	55.017	42.46	2588.15	2630.61
Case 2	Separately	30.3	97.37	30.3	44.57	270.45	44.57	55.017	-1934.6	2588.15	653.51
Case 3	Separately		97.37	30.3	53.3	133.18	53.3	70	-1325.4	2436.62	1111.22
Case 4	Jointly	10	94.99	10	53.3	133.18	53.3	70	636.8	2436.62	3073.4

Table 5.3 Results of Cases for Illustrative Example With Considering Virtual Bids.

	Offering Status (Separately/ Jointly)	FTR Offer Price ($/MWH)	FTR Cleared Power (MW)	FTR Auction Price ($/MWH)	DA Offer Price($/MWH)	DA Cleared Power (MW)	Virtual Gen. Bid Price ($/MWH)	Virtual Gen. Cleared Power (MW)	DALMP@ Bus 5 ($/MWH)	DA LMP@ Bus 2 ($/MWH)	FTR Profit ($)	Virtual Bids Profit ($)	DA Profit ($)	Total Profit ($)
Case 1	Separately	10	94.99	10	44.57	69.38	55.017 @ bus 2 44.57 @ bus 5	0.62 @ bus 2 200 @ bus 5	44.57	55.017	42.46	2929.55	663.97	3636
Case 2	Separately	30.3	97.37	30.3	44.57	69.38	55.017 @ bus 2 44.57 @ bus 5	0.62 @ bus 2 200 @ bus 5	44.57	55.017	-1934.65	2929.55	663.97	1658.87
Case 3	Separately		97.37	30.3	53.3	0	70 @ bus 2 0 @ bus 5	77.564 @ bus 2 0 @ bus 5	53.3	70	-1325.4	3102.55	0	1777.15
Case 4	Jointly	10	94.99	10	53.3	0	70 @ bus 2 0 @ bus 5	77.564 @ bus 2 0 @ bus 5	53.3	70	636.8	3102.55	0	3739.3

Figure 5.12 summarizes the comparison between these two results. As shown, virtual bid assists the MP to increase the FTR value with lower cost in the DA market and maximize its total profit. In other words, virtual bidding provides a noticeable opportunity for MP to increase the DA market profit and raise the FTR value more economically.

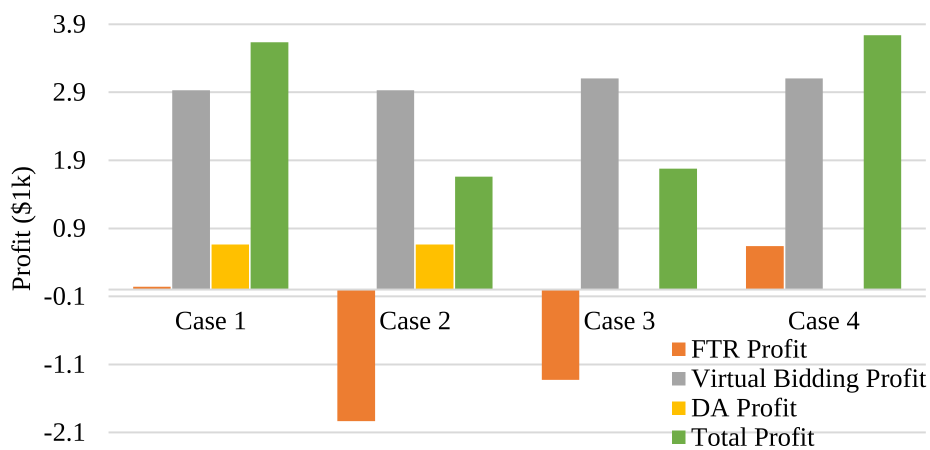


Figure 5.11 MP’s FTR profit, virtual bidding profit, DA market, and Total profit in different cases.

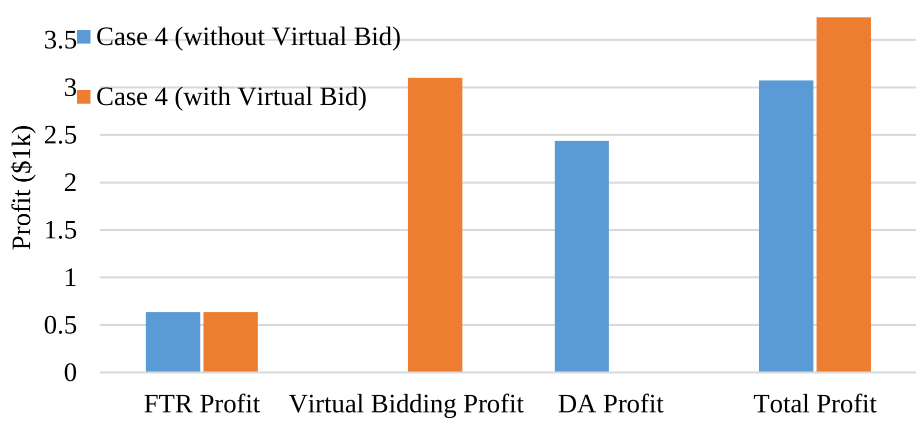


Figure 5.12 MP’s profit from FTR, virtual bidding, physical generation, and Total profit in Case 4 with and without employing virtual bids.

5.6. CASE STUDY

To demonstrate the effectiveness of the proposed joint offering strategy model and the value of utilizing the virtual bidding, Model ((5.30) – (5.31)) is solved for the strategic GenCo participating in the FTR auction and DA market in the 24-bus test system [82].

5.6.1. Data and Setups. Many ISOs in the US publish some of the historical market data such the market clearing results, historical bids and offers, and etc. for different electricity markets [94 – 98]. Such information may be used by the strategic MP to formulate, estimate and forecast the parameters needed for the decision making of the MP.

Table 5.4 FTR offers/bids of all MPs in the FTR auction for 24-bus system.

FTR #	Source (bus #)	Sink (bus #)	Status	Bid Price ($/MWH)	Bid Quantity (MW)	FTR #	Source (bus #)	Sink (bus #)	Status	Bid Price ($/MWH)	Bid Quantity (MW)
1	23	12	Seller	3	50	21	12	9	Seller	8	120
2	23	13	Seller	3	80	22	11	10	Seller	7	140
3	23	12	Buyer	*Variable*	*Variable*	23	24	3	Seller	6	120
4	23	12	Buyer	15	100	24	24	3	Buyer	*Variable*	*Variable*
5	23	12	Buyer	10	120	25	24	3	Buyer	13	50
6	23	13	Buyer	15	110	26	24	3	Buyer	14	75
7	23	13	Buyer	*Variable*	*Variable*	27	14	11	Seller	4	190
8	23	13	Buyer	9	90	28	15	16	Seller	3	120
9	16	14	Buyer	*Variable*	*Variable*	29	7	8	Buyer	*Variable*	*Variable*
10	16	14	Buyer	11	200	30	7	8	Seller	7.5	120
11	15	21	Buyer	*Variable*	*Variable*	31	7	8	Buyer	15	60
12	16	14	Buyer	12	150	32	24	15	Seller	4	240
13	16	14	Seller	4	100	33	22	21	Buyer	*Variable*	*Variable*
14	15	21	Buyer	11.5	300	34	12	10	Buyer	12	200
15	15	21	Buyer	10	120	35	12	10	Seller	6.5	80
16	15	21	Seller	3.5	50	36	16	19	Seller	8	100
17	17	16	Seller	4	60	37	17	18	Buyer	10.5	200
18	22	17	Buyer	*Variable*	*Variable*	38	17	22	Seller	5.5	150
19	17	16	Buyer	9.5	160	39	11	10	Buyer	15	50
20	11	9	Seller	3.5	105	40	24	15	Buyer	12.5	75

In this work, all data are selected based on generator characteristics [39] and financial constraints [23] to be aligned with real-world practices. It is assumed that 16 sellers and 24 buyers submit their offers and bids into the FTR auction, as exemplified in Table 5.4. The strategic MP plans to purchase eight FTRs from different $sink$ and $source$ buses in this auction. Furthermore, the strategic MP is assumed to own 7 generating units in different locations of the system; their maximum capacities and marginal costs are listed in Table 5.5.

Table 5.5 Strategic generating units data.

Gen #	$\overline{\boldsymbol{P}}_{tib}^{S}$ (MW)	$\boldsymbol{\lambda}_{tib}^{S}$ (\$/MWH)	(Bus #)
G1	76	15	1
G2	76	15	2
G3	400	7	7
G4	70	4	13
G5	197	20	16
G6	155	13	21
G7	155	13	23

Table 5.6 Generation units’ offer quantities and prices.

Gen #	$\overline{\boldsymbol{P}}_{tjb}^{G}$ (MW)	$\boldsymbol{\lambda}_{tjb}^{G}$ (\$/MWH)	(Bus #)	Gen #	$\overline{\boldsymbol{P}}_{tjb}^{G}$ (MW)	$\boldsymbol{\lambda}_{tjb}^{G}$ (\$/MWH)	(Bus #)
G1	21	16	1	G14	12	27	15
G2	21	16	1	G15	155	13	15
G3	21	16	1	G16	76	15	15
G4	21	16	2	G17	70	4	18
G5	90	18	2	G18	70	4	22
G6	90	22	2	G19	70	4	22
G7	90	22	7	G20	70	4	22
G8	155	13	7	G21	70	4	22
G9	155	13	13	G22	90	22	22
G10	12	27	13	G23	155	13	22
G11	12	27	15	G24	90	22	23
G12	12	27	15	G25	197	20	23
G13	12	27	15				

Predicted offer quantities and prices for 25 other generators in DA market are summarized in Table 5.6. These are presumed to be the same for all periods of time. Locations and maximum bid quantities of 17 loads in this system are shown in Table 5.7, and the bid prices in different time periods are depicted in Figure 5.13. Note that three different bid price profiles used for different loads in different location.

Table 5.7 Load bid quantities and prices.

Load #	$\overline{P}^{D}_{tdk}$ (MW)	(Bus #)	Load #	$\overline{P}^{D}_{tdk}$ (MW)	(Bus #)
L1	105	1	L10	188	10
L2	92	2	L11	255	13
L3	172	3	L12	188	14
L4	73	4	L13	305	15
L5	71	5	L14	98	16
L6	133	6	L15	323	18
L7	119	7	L16	174	19
L8	165	8	L17	126	20
L9	167	9			

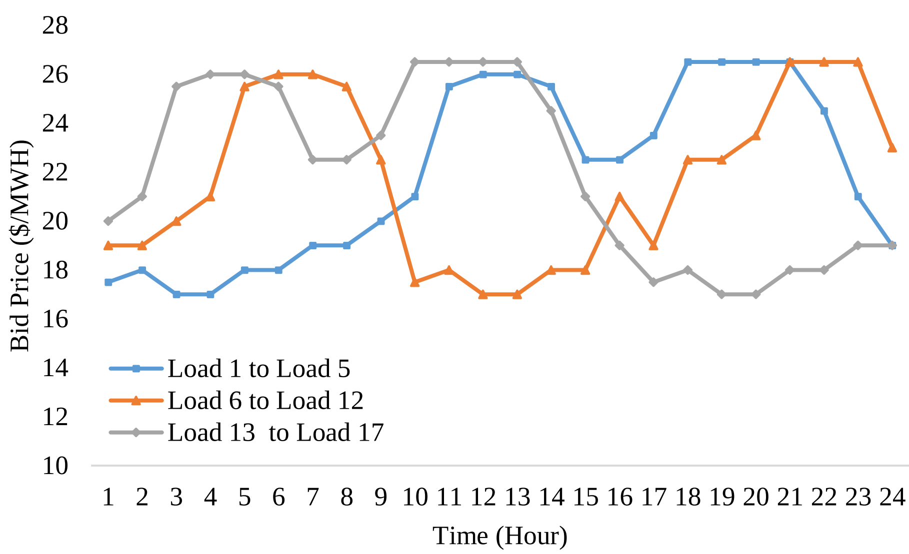


Figure 5.13 Load bid price profile.

5.6.2. Results and Discussion. The offering strategy problem is solved for the four designed cases introduced in the previous section, and the models are tested for the strategic MP with and without virtual bidding capability. Figure 5.14 shows the GenCo's profits in FTR auction, DA market and its total profit when the virtual bidding capability is not considered. Inaccurate DA LMPs forecast causes lower FTR profits in Case 2 and Case 3, which results in the lower total profit for these cases. The DA profit of MP is lower in Case 4 compared to Case 1; however, this is opposite for the FTR profit regarding these cases. This declares that the MP strategically loses a small amount of money in the DA market to increase the FTR value and optimize its total profit.

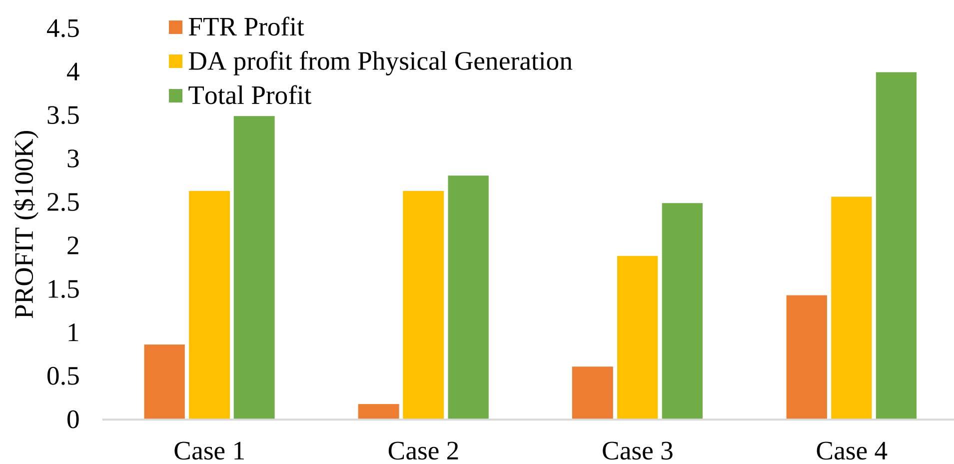


Figure 5.14 MP's profits in FTR auction, DA market as well as its total profit without considering the virtual bids.

Applying the virtual bidding, MP finds more opportunities to raise the FTR value and maximize its total profit. More specifically, Figure 5.15 presents the MP's profits from both physical generation and virtual bidding in DA market are higher in Case 1 than in Case 4. However, with this strategy, MP increases its FTR profit from $85k to approximately $265k, and as a result, makes more total profit. Note that it is assumed that the MP submits its virtual transactions from various locations (buses 3, 7, 11, 14, 17, and 22 in this study), and the forecasted real-time LMPs are assumed to be $20/MWH for all time periods.

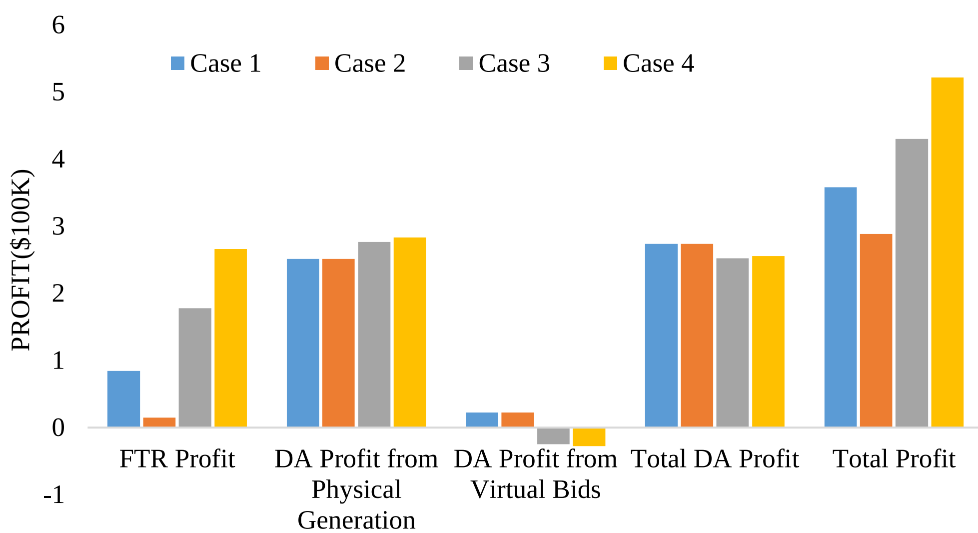


Figure 5.15 MP's profits from FTR, virtual bidding, physical generation along with its total profit.

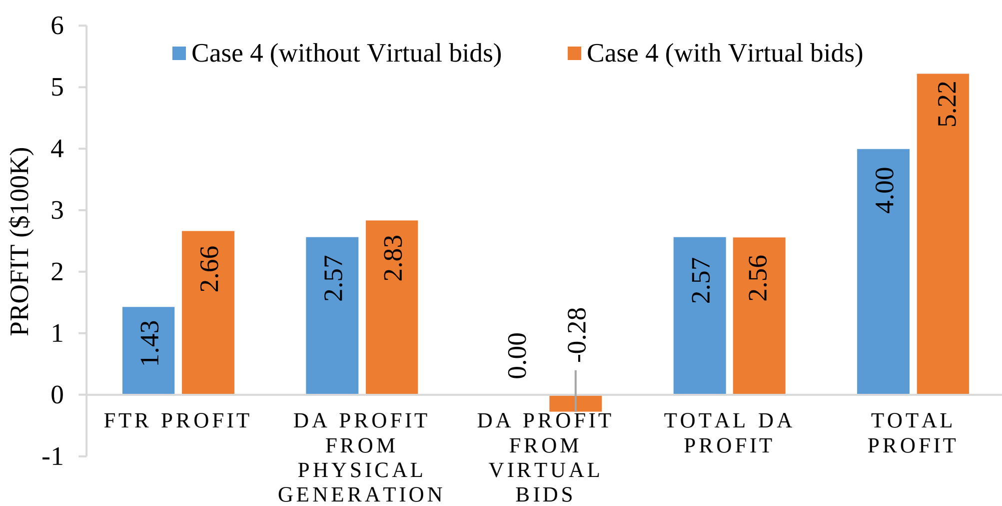


Figure 5.16 MP's profits from FTR, virtual bidding, and physical generation as well as its total profit in Case 4 with two tests (with and without considering virtual bids).

Comparing Case 4 from two tests (with and without virtual bidding) in Figure 5.16 depicts that the presence of virtual bids can help the MP manipulate the FTR value and increase the FTR profit and improve the DA market profit.

5.7. SECTION SUMMARY

This section's initial goal was to demonstrate the potential for FTR value manipulation through the submission of virtual bids in the DA market, which enables MPs to plan their strategy while taking into account a wider range of options. Then, it offered a novel two-stage bi-level joint offering strategy model for strategic GenCo that participated in both the FTR auction and the DA market, which served as a systematic framework to examine the likelihood of such manipulation. The proposed model enables this MP to use virtual bids in addition to deciding on the GenCo's physical generation because it is flexible enough to be either load or generation at different nodes of the network, which affects the FTR value and the MP's offering strategy's overall performance in both markets. After that, it demonstrated how the outcomes of the FTR auction affected the strategic GenCo's decision to offer in the DA market by examining how the GenCo behaves when they participate in both markets separately and jointly. Furthermore, a number of case studies, which are intended to compare with current techniques, demonstrate the effectiveness of the proposed model in creating an improved offering strategy, and show the possibility for a strategic MP to achieve higher total profits than the sum of profits in the FTR auction and DA market using separately developed strategies that have been described in the literature. In summary, the conclusions of this work are listed below.

a) A strategic GenCo faces complicated decision making due to the competing goals. It must delicately balance multiple objectives in the decision-making, such as (a) the tradeoff between the profits in FTR auction and the DA market due to the impact of DA LMP on FTR revenue; (b) tradeoff between profits of virtual bids and physical generation in the DA market due to both affecting DA LMPs; and (c) tradeoff between the FTR quantity and its impact on FTR auction price as both relate to FTR profit.

b) Based on the proposed model, the MP may choose a tactic that, by using virtual bids and its physical generation, can make higher profits through joint participation in FTR and DA markets. In fact, virtual bidding can create an opportunity for MP to increase the FTR value by manipulating the DA LMP at specific locations of the system. In some cases, manipulated DA LMP can result in reduced or negative profit from virtual bidding. Despite the resulting profit in DA market is reduced, the profit from FTR market is much increased and so is the total profit.

6. CONCLUSION

6.1. SUMMARY OF CONTRIBUTIONS

In Section 3, the decision-making process for risk-averse virtual bidder in the day-ahead market is comprehensively studied, and a robust max-min bi-level optimization model is presented to optimize the bidding strategy for his player [99]. The bi-level problem is converted into a mixed integer linear problem using the big-M approach, the duality theorem, Karush–Kuhn–Tucker optimality conditions, and strong duality theory. Since the quasi day-ahead market is represented by the proposed model's lower level subproblem, a virtual bidder can simulate the market clearing process and make bid decisions that are in its best interests. Given the uncertainty of opponents' strategies and real-time market pricing, a virtual bidder can therefore successfully compromise through the bid price between the quantity of cleared virtual bids and the affected price difference between the day-ahead and real-time markets. Real-time price is the most important uncertain parameter that the virtual bidder must take into account while making a decision, according to numerical data and sensitivity analysis performed in Section 3. Furthermore, when utilizing the proposed model in Section 3 for the virtual bidder instead of the deterministic approach, a risk-averse player can always make more money in the worst-case scenario, and the improvement in profits rises rapidly as the level of uncertainty rises.

The bi-level model and solution procedure proposed in Section 4 enables physical market participants with virtual bidding capabilities to maximize their overall profit in the participation of both physical assets and virtual bidding [100]. Through the use of scenarios-based modeling, uncertainty in rivals' offers and bids as well as real-time market prices has been taken into account. Furthermore, the risk associated with the market participant's various decisions has been quantified using the conditional value at risk (CVaR) metric. The suggested model's ability to determine the strategic player's optimal decisions is demonstrated by the simulation results, and employing the given models, the strategic asset-owned market participant is able to balance the profits from physical generation and virtual bids by selecting the optimal amount of physical and virtual transactions and controlling how they affect the day-ahead price. To test the proposed model, deterministic and stochastic case studies are defined in Section 4. A case study on a deterministic situation demonstrates a few optimal tactics that make use of virtual transactions to affect the price of day-ahead in a way that increases the profit from physical generation. For a stochastic situation, case studies show how the suggested method enables the strategic MP to choose a risk level that achieve a balance between the expected profit across all scenarios and the profit volatility in those scenarios.

For the strategic generating company with virtual bidding capability engaging in both the financial transmission right (FTR) auction and the day-ahead market, Section 5 presents a joint bidding strategy approach [101]. In this section, it is first shown that virtual bids can be employed to modify the financial transmission right values using a straightforward example. Next, the strong duality theory and Karush–Kuhn–Tucker optimality conditions are used to gradually create the suggested model. Additionally, a number of scenarios are created to demonstrate the model's applicability and the advantages of incorporating virtual bidding into the market participant's offering strategy decision-making process. It is shown that a strategic generating company must make difficult decisions as a result of competing goals. In making decisions, it must delicately derive a balance between a number of goals, including (a) the profits from the FTR auction and the day-ahead market due to the impact of the day-ahead prices on FTR revenue, (b) the profits from virtual bids and physical generation in the day-ahead market due to both affecting day-ahead prices, and (c) the profits from the FTR quantity and its effect on the FTR auction price as both relate to FTR profit. Additionally, the market player may decide on a strategy based on the suggested model that, by utilizing virtual bids and its physical generation, can generate larger profits through joint participation in FTR and day-ahead markets. In fact, by adjusting the day-ahead price at particular nodes in the system, virtual bidding might give market participant the chance to raise the FTR value. In some circumstances, altered day-ahead price can cause virtual bidding profits to be lowered or even negative. Despite the fact that the resulting profit in the day-ahead market is lower, the profit from the FTR market is significantly higher which consequently increases the overall profit.

6.2. FUTURE WORKS

There are some further works that could be viewed as future contributions to this project. First, the lower level of the models can employ the unit commitment model. Due to the lower level being a mixed integer problem and the fact that the Karush-Kuhn-Tucker and strong duality theory are not satisfied, this makes the solution more difficult.

The uncertainties related to other players' market offers and current prices might be taken into account to further broaden the scope of the model described in Section 5. In this manner, the integer variables would make up the second stage of the model, and the model should be solved using novel techniques such as column and constraint generation (CC&G).

The market participant can use a few additional variables to strengthen its plan of action and increase profits. These parameters could include the minimum ramp-up and ramp-down times, and etc. that have not been considered in this study. Additionally, the structure of the actual market may assist the market participant in creating a more effective bidding strategy. For instance, in the typical day-ahead electricity market, the unit commitment problem runs for 36 hours of the next day, while the economic dispatch problem utilizes the first 24 hours of the unit commitment output. The overlapped periods between market participants' decisions on two consecutive days may therefore help the market player in creating the best possible strategy.

The manipulative behaviors for different market participants in various markets were introduced in this work. However, the market monitoring operator (MMO) can look into this issue and establish new market regulations to stop these kinds of manipulative decisions.

APPENDIX

DETAIL FORMULATION FOR SECTION 5

PART A1) Mathematical Problem with Equilibrium Constraints (MPEC) model for the first stage problem.

Objective Function (5.1) (A1.1)

Subject to:

Constraints (5.2), (5.3), (5.9) and (5.10) (A1.2)

$$-\rho_e^s + \overline{\tau}_e^S - \underline{\tau}_e^S + MCP_e = 0, \quad \forall e \tag{A1.3}$$

$$-\rho_f + \overline{\tau}_f - \underline{\tau}_f + MCP_f = 0, \forall f \in \{N_{pur} - e\} \tag{A1.4}$$

$$\sigma_c + \overline{\tau}_c - \underline{\tau}_c - MCP_c = 0, \quad \forall c \in N_{sell} \tag{A1.5}$$

$$0 \le FTR_e^{Sbid} - FTR_e^s \perp \overline{\tau}_e^S \ge 0, \qquad \forall e \tag{A1.6}$$

$$0 \le FTR_e^s \perp \underline{\tau}_e^S \ge 0, \qquad \forall i \tag{A1.7}$$

$$0 \le \overline{FTR}_f - FTR_f \perp \overline{\tau}_f \ge 0, \qquad \forall f \tag{A1.8}$$

$$0 \le FTR_f \perp \underline{\tau}_f \ge 0, \qquad \forall f \tag{A1.9}$$

$$0 \le \overline{FTR}_c - FTR_c \perp \overline{\tau}_c \ge 0, \quad \forall c \in N_{sell} \tag{A1.10}$$

$$0 \le FTR_c \perp \underline{\tau}_c \ge 0, \quad \forall c \in N_{sell} \tag{A1.11}$$

$$0 \le \overline{F}_l - LF_l^{ex} - LF_l \perp \overline{\xi}_l \ge 0, \quad \forall l \tag{A1.12}$$

$$0 \le \overline{F}_l + LF_l^{ex} + LF_l \perp \underline{\xi}_l \ge 0, \quad \forall l \tag{A1.13}$$

In (A1), the nonlinear objective function is the same as in Model ((5.1) – (5.11)). Constraint (A.2) replicates (5.2), (5.3), (5.9) and (5.10) constraints. The first derivatives of the Lagrangian function with respect to the decision variables are shown in (A1.3) – (A1.5), and the nonlinear complementarity constraints that result from the inequality constraints of the LL subproblem of Model ((5.1) – (5.11)) are shown in (A1.6) – (A1.13).

PART A2) Mathematical Problem with Equilibrium Constraints (MPEC) model for the second stage problem.

Objective Function (5.12) (A2.1)

Subject to:

Constraints (5.13) – (5.19) (A2.2)

$$\alpha_{tib}^{s} - LMP_{tn} + \overline{\mu}_{tib}^{S} - \underline{\mu}_{tib}^{S} = 0, \forall t, i \in \psi_n, b \quad \text{(A2.3)}$$

$$\lambda_{tjb}^{g} - LMP_{tn} + \overline{\mu}_{tjb}^{G} - \underline{\mu}_{tjb}^{G} = 0, \forall t, j \in \psi_n, b \quad \text{(A2.4)}$$

$$-\lambda_{tdk}^{d} + LMP_{tn} + \overline{\mu}_{tdk}^{D} - \underline{\mu}_{tdk}^{D} = 0, \qquad \forall t, d \in \psi_n, k \quad \text{(A2.5)}$$

$$\alpha_{tv}^{bidG} - LMP_{tn} + \bar{\mu}_{tv}^{Vg} - \underline{\mu}_{tv}^{Vg} = 0, \forall t, v \in \psi_n \quad \text{(A2.6)}$$

$$-\alpha_{tv}^{bidD} + LMP_{tn} + \bar{\mu}_{tv}^{Vd} - \underline{\mu}_{tv}^{Vd} = 0, \qquad \forall t, v \in \psi_n \quad \text{(A2.7)}$$

Constraints (5.15) and (5.22) and (5.23) (A2.8)

$$0 \leq P_{tib}^{S} \perp \underline{\mu}_{tib}^{S} \geq 0, \quad \forall t, i, b \quad \text{(A2.9)}$$

$$0 \leq P_{tib}^{Sbid} - P_{tib}^{S} \perp \overline{\mu}_{tib}^{S} \geq 0, \quad \forall t, i, b \quad \text{(A2.10)}$$

$$0 \leq P_{tjb}^{g} \perp \underline{\mu}_{tjb}^{G} \geq 0, \quad \forall t, j, b \quad \text{(A2.11)}$$

$$0 \leq \overline{P}_{tjb}^{G} - P_{tjb}^{g} \perp \overline{\mu}_{tjb}^{G} \geq 0, \quad \forall t, j, b \quad \text{(A2.12)}$$

$$0 \leq P_{tdk}^{d} \perp \underline{\mu}_{tdk}^{D} \geq 0, \quad \forall t, d, k \quad \text{(A2.13)}$$

$$0 \le \overline{P}_{tdk}^{D} - P_{tdk}^{d} \perp \overline{\mu}_{tdk}^{D} \ge 0, \ \ \forall t, d, k \tag{A2.14}$$

$$0 \le V_{tv}^{DAg} \perp \underline{\mu}_{tv}^{Vg} \ge 0, \quad \forall t, v \tag{A2.15}$$

$$0 \le V_{tv}^{DAd} \perp \underline{\mu}_{tv}^{Vd} \ge 0, \quad \forall t, v \tag{A2.16}$$

$$0 \le V_{tv}^{bidG} - V_{tv}^{DAg} \perp \bar{\mu}_{tv}^{Vg} \ge 0, \quad \forall t, v \tag{A2.17}$$

$$0 \le V_{tv}^{bidD} - V_{tv}^{DAd} \perp \bar{\mu}_{tv}^{Vd} \ge 0, \quad \forall t, v \tag{A2.18}$$

$$0 \le F_{tl} + \overline{F}_{l} \perp \underline{\vartheta}_{tl} \ge 0 \quad \forall t, l \tag{A2.19}$$

$$0 \le \overline{F}_{l} - F_{tl} \perp \overline{\vartheta}_{tl} \ge 0 \quad \forall t, l \tag{A2.20}$$

In (A2), the objective function and the UL constraints (5.13) – (5.19) are duplicated in (A2.1) and (A2.2). The first derivative of Lagrangian function with respect to the decision variables are denoted by (A2.3) – (A2.7). The equality constraints (5.21), (5.28), and (5.29) are summarized in (A2.8). Constraints (A2.9) – (A2.20) represent the nonlinear complementarity constraints regarding the inequality constraints (5.22) – (5.27).

PART A3) To linearize the first nonlinear term of the objective function (5.1 (or A1.1)), the SDT approach is employed. Thus, applying these methods to (A1) results in the following model with linear constraints.

$$\boldsymbol{OF_1} = \underset{\Omega_1^{FTR}, \Omega_2^{FTR}}{\text{Minimize}} \sum_{t} \Bigg(-\sum_{f} \rho_f FTR_f + \sum_{f} \sigma_c FTR_c + \sum_{f} \overline{\tau}_f \overline{FTR}_f + \sum_{c} \overline{\tau}_c \overline{FTR}_c + \sum_{tl} \left(\overline{\xi}_l + \underline{\xi}_l \right) \overline{F}_l - \left(LMP_{t,sink} - LMP_{t,source} \right) FTR_e^s \Bigg) \tag{A3.1}$$

Subject to:

Constraints (A1.2) – (A1.5) (A3.2)

Linearized form of (A1.6) – (A1.13) (A3.3)

Moreover, complementarity nonlinear constraints can be linearized using Big M method. Thus, each of the equations of $0 \leq X_{ti} \perp d_{ti}(x) \geq 0$ can be rewritten as follows.

$$0 \leq X_{ti} \leq M_{ti}\, \omega_{ti},$$

$$0 \leq d_{ti}(x) \leq (1 - \omega_{ti})\, M_{ti}$$

where M_{ti} is a large number and ω_{ti} is a binary variable.

Applying SDT and Big M methods, the equivalent linear formulation of the problem (A2) is obtained as follows.

$$\boldsymbol{OF_2} = \underset{\Omega_1^{DA}, \Omega_2^{DA}}{\text{Minimize}} \left[\sum_{tib} \left(\lambda_{tib}^{S} P_{tib}^{s} + \sum_{t(v \in \psi_n)} \lambda_{tn}^{RT} \left(V_{tv}^{DAg} - V_{tv}^{DAd} \right) \right) \right.$$
$$+ \left(\sum_{tjb} \lambda_{tjb}^{g} P_{tjb}^{g} + \sum_{tjb} \overline{\mu}_{tjb}^{G} \overline{P}_{tjb}^{G} - \sum_{tdk} \lambda_{tdk}^{d} P_{tdk}^{d} \right. \tag{A3.4}$$
$$\left. \left. + \sum_{tdk} \overline{\mu}_{tdk}^{D} \overline{P}_{tdk}^{D} + \sum_{tl} \left(\underline{\vartheta}_{tl} + \overline{\vartheta}_{tl} \right) \overline{F}_{l} \right) \right]$$

Subject to:

Constraints (A2.2) – (A2.8) (A3.5)

Linearized form of (A2.9) – (A2.20) (A3.6)

BIBLIOGRAPHY

[1] M. Ilic, F. Galiana, and L. Fink, *Power systems restructuring: engineering and economics*. Springer Science & Business Media, 2013.

[2] I. Dyner, and E. R. Larsen, "From planning to strategy in the electricity industry," *Energy Policy*, vol. 26, pp. 1145-1154, 2001.

[3] D. Finon, T. A. Johnson, and A. Midttun, "Challenges when electricity markets face the investment phase", *Energy Policy*, vol. 32, pp. 1355-1362, 2004.

[4] M. Armstrong, S. Cowan, and J. Vickers, *Regulatory Reform*, MIT Press, Cambridge, MA. 1994.

[5] D. S. Kirschen and G. Strbac, *Fundamentals of power system economics*. John Wiley & Sons, 2018.

[6] G. Brown, and M. B. Johnson, "Public Utility Pricing and Output Under Risk, " *The American Economic Review*, vol. 59, no. 1, pp. 119-128, 1968.

[7] W. L. Megginson and J. M. Netter, “From state to market: A survey of empirical studies on privatization,” *Journal of economic literature*, vol. 39, no. 2, pp. 321–389, 2001.

[8] J. P. Pfeifenberger, P. Q. Hanser, and P. R. Ammann, "What's the Cards for Distributed Resources?," *The Energy Journal, Distributed Resources,* Special Issue, 1997.

[9] H. L. Willis and L. Philipson, *Understanding electric utilities and deregulation*. CRC Press, 2018.

[10] Li, Gong, Jing Shi, and Xiuli Qu. "Modeling methods for GenCo bidding strategy optimization in the liberalized electricity spot market–A state-of-the-art review." *Energy* 36, no. 8, 4686-4700, 2011.

[11] D. W. Bunn, “Structural and behavioral foundations of competitive electricity prices,” *in Modeling Prices in Competitive Electricity Markets*, D. W. Bunn, Ed. New York: John Wiley & Sons, pp. 1–17, 2004.

[12] T. W. Berrie, *Electricity Economics and Planning*, P. Peregrinus Ltd., 1993.

[13] M. Shahidehpour, H. Yamin, and Z. Li, *Market Operations in Electric Power Systems, Forecasting, Scheduling, and Risk Management*, Wiley-IEEE Press, 2003.

[14] A. J. Conejo, F. D. Galiana, J. M. Arroyo, R. García-Bertrand, C. W. Chua, and M. Huneault, "Economic inefficiencies and cross-subsidies in an auction-based electricity pool", *IEEE Transactions on Power Systems*, vol. 18, no. 1, pp. 221-228, Feb. 2003.

[15] M. L. Baughman, S. N. Seddiqi, and J. W. Zarnikau, "Advanced pricing in electrical systems— Part I: Theory," *IEEE Transactions Power Systems*, vol. 12, pp. 489–495, Feb. 1997.

[16] Y. Ren, and F. D. Galiana, "Pay-as-bid versus marginal pricing-part I: strategic generator offers," *IEEE Transactions Power Systems*, vol. 19, pp. 1771–1776, Nov. 2004.

[17] P. R. Gribik, G. A. Angelidis, and R. R. Kovacs, "Transmission access and pricing with multiple separate energy forward markets," *IEEE Transactions on Power Systems*, vol. 14, pp. 865– 876, Aug. 1999.

[18] OMEL: Market operator of the electricity market of mainland Spain Market rules. [Online]. Available: http://www.omel.es/en/reglas_contrato/mreglasconadhesionfr.htm.

[19] R. S. Fang and A. K. David, "Transmission congestion management in an electricity market," *IEEE Transactions on Power Systems*, vol. 14, pp. 877–883, Aug. 1999.

[20] M. Huneault and F. D. Galiana, "A survey of the optimal power flow literature," *IEEE Transactions on Power Systems*, vol. 6, pp. 762–770, May 1991.

[21] F. Li and R. Bo, "DCOPF-Based LMP Simulation: Algorithm, Comparison With ACOPF, and Sensitivity," *IEEE Transactions on Power Systems*, vol. 22, no. 4, pp. 1475-1485, Nov. 2007.

[22] A. J. Conejo, M. Carri´on, J. M. Morales, et al., *Decision making under uncertainty in electricity markets*, vol. 1. Springer, 2010.

[23] Sevi Baltaoglu, Lang Tong, and Qing Zhao, "Algorithmic bidding for virtual trading in electricity markets," *IEEE Transactions on Power Systems*, vol. 34, no. 1, pp. 535–543, 2018.

[24] Prabavathi, M., and R. Gnanadass. "Energy bidding strategies for restructured electricity market." *International Journal of Electrical Power & Energy Systems*, 64, 956-966, 2015.

[25] Interconnection P.J.M., "Virtual transactions in the PJM energy markets," https://www.pjm.com/~/media/committeesgroups/committees/mc/ , 2015.

[26] Tao Li and Mohammad Shahidehpour, “Strategic bidding of transmission-constrained gencos with incomplete information,” *IEEE Transactions on Power Systems*, vol. 20, no. 1, pp. 437–447, 2005.

[27] Jianxiao Wang, Haiwang Zhong, Wenyuan Tang, Ram Rajagopal, Qing Xia, Chongqing. Kang, and Yi Wang, “Optimal bidding strategy for microgrids in joint energy and ancillary service markets considering flexible ramping products,” *Applied Energy*, vol. 205, pp. 294–303, 2017.

[28] A. J. Conejo, F. J. Nogales, and J. M. Arroyo, “Price-taker bidding strategy under price uncertainty,” *IEEE Transactions on Power Systems*, vol. 17, no. 4, pp. 1081–1088, Nov. 2002.

[29] J. M. Morales, A. J. Conejo, and J. P´erez-Ruiz, “Short-term trading for a wind power producer,” *IEEE Transactions on Power Systems*, vol. 25, no. 1, pp. 554–564, Feb. 2010.

[30] B. Mohammadi-Ivatloo, H. Zareipour, N. Amjady, and M. Ehsan, “Application of information-gap decision theory to risk-constrained self scheduling of gencos,” *IEEE Transactions on Power Systems*, vol. 28, no. 2, pp. 1093–1102, May 2013.

[31] S. I. Vagropoulos and A. G. Bakirtzis, “Optimal bidding strategy for electric vehicle aggregators in electricity markets,” *IEEE Transactions on Power Systems*, vol. 28, no. 4, pp. 4031–4041, 2013.

[32] P. Kanakasabapathy and K. S. Swarup, “Bidding strategy for pumped storage plant in pool-based electricity market,” *Energy conversion and Management*, vol. 51, no. 3, pp. 572–579, 2010.

[33] N. Lu, J. H. Chow, and A. A. Desrochers, “Pumped-storage hydro-turbine bidding strategies in a competitive electricity market,” *IEEE Transactions on Power Systems*, vol. 19, no. 2, pp. 834–841, 2004.

[34] H. Khaloie, A. Abdollahi, M. Shafie-Khah, P. Siano, S. Nojavan, A. Anvari-Moghaddam, and J. P. Catal˜ao, “Co-optimized bidding strategy of an integrated wind-thermal-photovoltaic system in deregulated electricity market under uncertainties,” *Journal of Cleaner Production*, vol. 242, p. 118434, 2020.

[35] Z. Xu, Z. Hu, Y. Song, and J. Wang, “Risk-averse optimal bidding strategy for demand-side resource aggregators in day-ahead electricity markets under uncertainty,” *IEEE Transactions on Smart Grid*, vol. 8, no. 1, pp. 96–105, 2015.

[36] A. A. Thatte, D. E. Viassolo, and L. Xie, “Robust bidding strategy for wind power plants and energy storage in electricity markets,” *in 2012 IEEE Power and Energy Society General Meeting*, pp. 1–7, IEEE, 2012.

[37] Sebastian de la Torre, Jose M. Arroyo, Antonio J. Conejo, and Javier Contreras, “Price maker self-scheduling in a pool-based electricity market: A mixed integer LP approach,” *IEEE Transactions on Power Systems*, vol. 17, no. 4, pp. 1037–1042, 2002.

[38] Mario V. Pereira, Sergio Granville, Marcia H. Fampa, Rafael Dix, and Luiz A. Barroso, “Strategic bidding under uncertainty: A Binary Expansion Approach,” *IEEE Transactions on Power Systems*, vol. 20, no. 1, pp. 180–188, 2005.

[39] Carlos Ruiz and Antonio J. Conejo, “Pool strategy of a producer with endogenous formation of locational marginal prices,” *IEEE Transactions on Power Systems*, vol. 24, no. 4, pp. 1855–1866, 2009.

[40] Evaggelos G. Kardakos, Christos K. Simoglou, and Anastasios G. Bakirtzis, “Optimal bidding strategy in transmission-constrained electricity markets,” *Electric Power Systems Research*, vol. 109, pp. 141–149, 2014.

[41] M. S .H Nizami, M. J. Hossain, BM R. Amin, and Edstan Fernandez, “A residential energy management system with bi-level optimization-based bidding strategy for day-ahead bi-directional electricity trading,” *Applied Energy*, vol. 261, p. 114322, 2020.

[42] Charles W. Richter and Gerald B. Sheble, “Genetic algorithm evolution of utility bidding strategies for the competitive marketplace,” *IEEE Transactions on power Systems*, vol. 13, no. 1, pp. 256–261, 1998.

[43] Miguel A. Plazas, Antonio J. Conejo, and Fransisco J. Prieto, “Multimarket optimal bidding for a power producer,” *IEEE Transactions on power Systems*, vol. 20, no. 4, pp. 2041–2050, 2005.

[44] Trine K. Boomsma, Nina Juul, and Stein-Eric. Fleten, “Bidding in sequential electricity markets: The nordic case,” *European Journal of Operational Research*, vol. 238, no. 3, pp. 797–809, 2014.

[45] Jose Iria, Filipe Soares, and Manuel Matos, “Optimal bidding strategy for an aggregator of prosumers in energy and secondary reserve markets,” *Applied Energy*, vol. 238, pp. 1361–1372, 2019.

[46] Cihan Babayigit, Patricio Rocha, and Tapas K. Das, “A two-tier matrix game approach for obtaining joint bidding strategies in FTR and energy markets,” *IEEE Transactions on power Systems*, vol. 25, no. 3, pp. 1211–1219, 2010.

[47] William W. Hogan, “Virtual bidding and electricity market design,” *Electricity Journal*, vol. 29, no. 5, pp. 33–47, 2016.

[48] Alan G. Isemonger, “The benefits and risks of virtual bidding in multi settlement markets,” *Electricity Journal*, vol. 19, no. 9, pp. 26 36, 2006.

[49] Metin Celebi, Attila Hajos, and Philip Q. Hanser, “Virtual bidding: the good, the bad and the ugly,” *Electricity Journal*, vol. 23, no. 5, pp. 16–25, 2010.

[50] Jalal Kazempour and Benjamin F. Hobbs, “Value of flexible resources, virtual bidding, and self-scheduling in two-settlement electricity markets with wind generation—part i: principles and competitive model,” *IEEE Transactions on Power Systems*, vol. 33, no. 1, pp. 749–759, 2017.

[51] C. L. Prete, N. Guo, and U. V. Shanbhag, “Virtual bidding and financial transmission rights: an equilibrium model for cross-product manipulation in electricity markets,” *IEEE Transactions on Power Systems*, vol. 34, no. 2, pp. 953–967, 2018.

[52] W. Wang and N. Yu, “A machine learning framework for algorithmic trading with virtual bids in electricity markets,” *IEEE Power & Energy Society General Meetings*, pp. 1–5, 2019.

[53] Dongliag Xiao, W. Qiao, and Liyan Qu, “Risk-averse offer strategy of a photovoltaic solar power plant with virtual bidding in electricity markets,” *IEEE Power Energy Society Innovative Smart Grid Technical Conference*, pp. 1–5, 2019.

[54] H. Mehdipourpicha and R. Bo, “Risk-constrained bi-level optimization for virtual bidder bidding strategy in day-ahead electricity markets,” *IEEE Power & Energy Society General Meetings*, pp. 1–5, 2020.

[55] S. D. Ledgerwood and J. P. Pfeifenberger, “Using virtual bids to manipulate the value of financial transmission rights,” *Electricity Journal*, vol. 26, no. 9, pp. 9–25, 2013.

[56] Vasileios P. Gountis, Anastasios G. Bakirtzis , “Bidding strategies for electricity producers in a competitive electricity marketplace,” ,” *IEEE Transactions on Power Systems*, vol. 19, no. 1, pp. 356–365, 2004.

[57] Soroush Shafiee, Payam Zamani-Dehkordi, Hamidreza Zareipour, Andrew M. Knight, “Economic assessment of a price-maker energy storage facility in the Alberta electricity market,” *Energy*, vol. 111, pp. 537–547, 2016.

[58] Luis Baringo, Antonio J. Conejo, “Offering strategy of wind-power producer: A multi-stage risk-constrained approach,” *IEEE Transactions on Power Systems*, vol. 31, no. 2, pp. 1420–1429, 2015.

[59] Chanwit Boonchuay, Weerakorn Ongsakul, “Optimal risky bidding strategy for a generating company by self-organising hierarchical particle swarm optimisation,” *Energy Conversion and Management*, vol. 52, no. 2, pp. 1047–1053, 2011.

[60] Morteza Rahimiyan and Luis Baringo, “Strategic bidding for a virtual power plant in the day-ahead and real-time markets: A price-taker robust optimization approach,” *IEEE Transactions on Power Systems*, vol. 31, no. 4, pp. 2676–2687, 2015.

[61] Xuejiao Han, Evangelos G. Kardakos, Gabriela Hug, “A distributionally robust bidding strategy for a wind power plant,” *Electric Power Systems Research*, vol. 177, p. 105986, 2019.

[62] Xuejiao Han, Gabriela Hug, “A distributionally robust bidding strategy for a wind-storage aggregator,” *Electric Power Systems Research*, vol. 189, pp. 106745, 2020.

[63] Ana Baringo, Luis Baringo, “A stochastic adaptive robust optimization approach for the offering strategy of a virtual power plant,” *IEEE Transactions on Power Systems*, vol. 32, no. 5, pp. 3492–3504, 2016.

[64] Sajede Darvishi, Gholamhossein Sheisi, Jamshid Aghaei, “Bidding strategy of hybrid power plant in day-ahead market as price maker through robust optimization,” *International Transactions on Electrical Energy Systems*, vol. 30, no. 7, p. e12426, 2020.

[65] Bo Zeng, Houqi Dong, Ramteen Sioshansi, Fuqiang Xu, Ming Zeng, “Bilevel robust optimization of electric vehicle charging stations with distributed energy resources,” *IEEE Transactions on Industry Applications*, vol. 56, no. 5, pp. 5836–5847, 2020.

[66] Soroush Shafiee, Hamidreza Zareipour, Andrew M. Knight, “Developing bidding and offering curves of a price-maker energy storage facility based on robust optimization,” *IEEE Transactions on Smart Grid*, vol. 10, no. 1, pp. 650– 660, 2017.

[67] Hosna Khajeh, Asghar A. Foroud, Hooman Firoozi, “Robust bidding strategies and scheduling of a price-maker microgrid aggregator participating in a pool-based electricity market,” *IET Generation, Transmission & Distribution*, vol. 13, no. 4, pp. 468–477, 2018.

[68] A. G. Bakirtzis, N. P. Ziogos, A. C. Tellidou, and G. A. Bakirtzis, “Electricity producer offering strategies in day-ahead energy market with step-wise offers,” *IEEE Transactions on Power Systems*, vol. 22, no. 4, pp. 1804–1818, 2007.

[69] A. Baillo, M. Ventosa, M. Rivier, and A. Ramos, “Optimal offering strategies for generation companies operating in electricity spot markets,” *IEEE Transactions on Power Systems*, vol. 19, no. 2, pp. 745–753, 2004.

[70] V. Davatgaran, M. Saniei, and S. S. Mortazavi, “Optimal bidding strategy for an energy hub in energy market,” *Energy*, vol. 148, pp. 482–493, 2018.

[71] T. Li and M. Shahidehpour, “Risk-constrained FTR bidding strategy in transmission markets,” *IEEE Transactions on Power Systems*, vol. 20, no. 2, pp. 1014–1021, 2005.

[72] T. Li, M. Shahidehpour, and Z. Li, “Bidding strategy for FTR obligations in transmission markets,” *IEE Proceedings-Generation, Transmission and Distribution*, vol. 152, no. 3, pp. 422–428, 2005.

[73] D. Yang, A. Hallam, Y. Chen, X. Wang, and F. Yang, “Optimal bidding strategy for financial transmission right,” *in 2006 International Conference on Power System Technology*, pp. 1–6, 2006.

[74] G. Bautista and V. H. Quintana, “Complementarity-based models for financial transmission rights,” *in IEEE Power Engineering Society General Meeting*, 2005, pp. 440–446, 2005.

[75] L. Fan, J. Wang, R. Jiang, and Y. Guan, “Min-max regret bidding strategy for thermal generator considering price uncertainty,” *IEEE Transactions on Power Systems*, vol. 29, no. 5, pp. 2169–2179, 2014.

[76] John Birge, Ali Hortaçsu, Ignacia Mercadal, Michael Pavlin, “Virtual Bidders and Financial Transmission Rights in the MISO Electricity Market”, https://www.editorialexpress.com , May, 2013.

[77] Aharon Ben-Tal, Laurent El Ghaoui, Arkadi Nemirovski, *Robust Optimization*. Princeton, NJ, USA: Princeton Univ. Press, 2009.

[78] Jose Fortuny-Amat, Bruce McCarl, “A representation and economic interpretation of a two-level programming problem,” *Journal of Operation Research Society*, vol. 32, no. 9, pp. 783–792, 1981.

[79] X. Wang, F. Li, J. Dong, M. M. Olama, Q. Zhang, Q. Shi, B. Park, and T. Kuruganti, “Tri-level scheduling model considering residential demand flexibility of aggregated hvacs and evs under distribution lmp,” *IEEE Transactions on Smart Grid*, vol. 12, no. 5, pp. 3990–4002, 2021.

[80] A. J. Conejo and C. Ruiz, “Complementarity, not optimization, is the language of markets,” *IEEE Open Access Journal of Power and Energy*, vol. 7, pp. 344–353, 2020.

[81] Juan M. Morales, Antonio J. Conejo, Henrik Madsen, Pierre Pinson, Marco Zugno, *Integrating Renewables in Electricity Markets: Operational Problems*, vol. 205. New York, NY, USA: Springer Science & Business Media, 2013.

[82] Christos Ordoudis, Pierre Pinson, Juan M. M. Gonz´alez, Marco Zugno, "An updated version of the ieee rts 24-bus system for electricity market and power system operation studies," *Technical University of Denmark*, 2016.

[83] AIMMS. Available: https://www.aimms.com.

[84] The ILOG CPLEX, 2008. [Online]. Available: http://www.ilog.com/ products /cplex/.

[85] Rockafellar R. Tyrrell, Stanislav Uryasev, et al., "Optimization of conditional value-at- risk," *Journal of risk*, vol. 2, pp. 21–42, 2000.

[86] Steven A. Gabriel, Antonio J. Conejo, J. David Fuller, Benjamin F. Hobbs, and Carlos Ruiz, *Complementarity modeling in energy markets*, vol. 180. Springer Science & Business Media, 2012.

[87] Power Systems Test Case Archive, https://labs.ece.uw.edu/pstca/pf14 /pg_tca14bus.htm.

[88] Ray D. Zimmerman, Carlos E. Murillo-Sanchez, and Robert J. Thomas, "MATPOWER: Steady-State Operations, Planning and Analysis Tools for Power Systems Research and Education," *IEEE Transactions on Power Systems*, vol. 26, no. 1, pp. 12–19, Feb. 2011.

[89] R. Yan, G. Geng, Q. Jiang, and Y. Li, "Fast transient stability batch assessment using cascaded convolutional neural networks," *IEEE Transactions on Power Systems*, vol. 34, no. 4, pp. 2802–2813, 2019.

[90] F. Li and R. Bo, "Small test systems for power system economic studies," *in IEEE PES general meeting*, pp. 1–4, IEEE, 2010.

[91] T. K. Das, Patricio Rocha, and Cihan Babayigit, "A matrix game model for analyzing FTR bidding strategies in deregulated electric power markets," *International Journal of Electrical Power & Energy Systems*, vol. 32, no. 7, pp. 760–768, 2010.

[92] MISO Manual, BPM-004-r19, "Business Practices Manual Financial Transmission Rights (FTR) and Auction Revenue Rights (ARR)", https://www.misoenergy.org/api/documents/getbymediaid/34826 , 2018.

[93] M. Alomoush and S. Shahidehpour, “Generalized model for fixed transmission rights auction,” *Electric Power System Research*, vol. 54, no. 3, pp. 207–220, 2000.

[94] ERCOT: Available online: https://www.ercot.com/mktinfo

[95] PJM: Available online: https://www.pjm.com/markets-and-operations

[96] NE-ISO: Available online: https://www.iso-ne.com/markets-operations/markets

[97] MISO: Available online: https://www.misoenergy.org/markets-and-operations/#t=10&p=0&s=&sd=

[98] CAISO: Available online: https://www.caiso.com/market/

[99] H. Mehdipourpicha, S. Wang, and R. Bo, “Developing robust bidding strategy for virtual bidders in day-ahead electricity markets,” *IEEE Open Access Journal of Power and Energy*, vol. 8, pp. 329–340, 2021.

[100] H. Mehdipourpicha and R. Bo, “Optimal bidding strategy for physical market participants with virtual bidding capability in day-ahead electricity markets,” *IEEE Access*, vol. 9, pp. 85392–85402, 2021.

[101] H. Mehdipourpicha, R. Bo, and S. Wang, “Optimal offering strategy of GenCo with joint participation in FTR auction and day-ahead market considering virtual bidding,” *IEEE Transactions on Power Systems*, 2022.

VITA

Hossein Mehdipourpicha received his Bachelor of Science in Electrical Engineering from K. N. Toosi University of Technology (Iran) in September 2010 and his Master of Science in the same major from Iran University of Science and Technology (Iran) in November 2013. He started his Ph.D. at Missouri University of Science and Technology (Missouri S&T) in 2018. His research interests included power system optimization and economics, and electricity market simulation. He received the Doctor of Philosophy in Electrical Engineering from Missouri S&T in December 2022.