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Hybrid Power Plant Bidding Strategy for Electricity Market Participation

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I, Sahand Ghavidel Jirsaraie declare that this thesis, is submitted in fulfillment of the requirements for the award of doctor of philosophy, in the School of Electrical, Mechanical and Mechatronic Systems, Faculty of Engineering and Information Technology at the University of Technology Sydney.

This thesis is wholly my own work unless otherwise reference or acknowledged. In addition, I certify that all information sources and literature used are indicated in the thesis.

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Publications and Conference Contributions

The following publications are part of the thesis.

Peer-reviewed international journal publications

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[5] **S. Ghavidel***, M. Barani, A. Azizivahed, M. J. Ghadi, L. Li, and J. Zhang, "Hybrid power plant offering strategy to deal with the stochastic nature and outage of wind

generators," in *Electrical Machines and Systems (ICEMS)*, 2017 20th International Conference on, 2017, pp. 1-6: IEEE.

[6] **S. Ghavidel***, L. Li, J. Aghaei, T. Yu, and J. Zhu, "A review on the virtual power plant: Components and operation systems," in *IEEE International Conference on Power System Technology*, 2016: IEEE.

Abstract

In this thesis, the strategies of hybrid power plants (HPPs) in electricity markets to minimize the impacts of wind power uncertainties through storage and demand managements are investigated.

Firstly, a commercial Compressed Air Energy Storage (CAES) aggregator equipped with a simple cycle operation mode is correlated with a Wind Power Aggregator (WPA) as an HPP to participate in electricity markets. The WPA utilizes the CAES to tackle wind power forecasting errors and uncertainties associated with different electricity market prices, while CAES can get assistance from WPA to schedule its charging/discharging and simple cycle modes more economically. A three-stage stochastic decision-making method is formulated to model the proposed optimization problem. Besides, conditional value-at-risk (CVaR) is added to the model to control the financial risk of the problem and offer different operation strategies for different financial risk levels. It also provides both bidding quantity and bidding curves to be submitted to the electricity markets.

Secondly, an offering strategy with a three-stage stochastic programming is presented for an HPP, which includes a WPA and a Demand Response Aggregator (DRA). Three electricity markets are considered including DA, intraday, and balancing market for the joint operation of WPA and DRA as an HPP. The CVaR is also added to the HPP offering strategy to control the profit risk. The offering strategy for the second case study is tested in a wind farm and electricity market located in Spain. The result shows that the HPP offering strategy can effectively assist the balancing and outage problem of the WPA and increase the overall profit of the joint operation.

Finally, an HPP, including a CAES aggregator with a WPA is modeled considering network constraints. Three objective functions are considered including electricity market maximization, congestion management, and voltage stability improvement. In order to accurately model the WPA, pitch control ability is added to wind generator models to control the wind power curtailment level. Multi-objective Pareto front solutions are considered to optimize all the mentioned objective functions properly, and finally, the best solution is suggested using the fuzzy method. The proposed approach is tested on a realistic case study based on a wind farm and electricity market located in Spain, and the IEEE 57 bus test system is used to analyze the network constraint effects on the HPP scheduling for different objective functions.

Keywords: Hybrid Power Plant; Wind Power Aggregator; Demand Response Aggregator; Compressed Air Energy Storage Aggregator

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Nomenclature

Global abbreviations used in this thesis:

ADN	Active Distribution Network
BESS	Battery Energy Storage System
CAES	Compressed Air Energy Storage
CHP	Combined Heat And Power
CHP	Coupled with District Heating (CHP–DH)
CVaR	Conditional Value-at-Risk
CHPP	Commercial HPP
DA	Day-Ahead
DG	Distributed Generation
DR	Demand Response
DRP	Demand Response Provider
DRRs	Demand Response Resources
DSO	Distribution System Operator
EDLC	Electric Double-Layer Capacitors
EDLC	Electric Double-Layer Capacitors
EMS	Energy Management System
FERC	Federal Energy Regulatory Commission
FES	Flywheel Energy Storage
HPES	Hydraulic Pumped Energy Storage

HPP	Hybrid Power Plant
PEM	Point Estimate Method
PEVs	Plug-In Electric Vehicles
PHEVs	Plug-In Hybrid Electric Vehicles
SMES	Superconducting Magnetic Energy Storage
TSO	Transmission System Operator
THPP	Technical HPP
HPP	Hybrid Power Plant
WPA	Wind Power Aggregator

1 Introduction

1.1 Background and Research Question

Recently, the number of distributed generations (DGs) have been rapidly increased in electricity networks. Even though DGs have the capability of substituting the energy generated by conventional power plants, they require advanced technologies to safely and economically deliver energy to the system. With the high penetration of DGs, this attitude always causes the increasing total investment on the infrastructure and, in the long run, has an adverse impact on the DG integration [1, 2]. In order to find a solution to the mentioned issue, DGs must be incorporated by a current systematic arrangement which helps them to contribute simultaneously in different electricity markets. HPP is a concept that can be employed in accomplishing this objective [2]. The HPP aggregates many heterogeneous Distributed Energy Resources (DERs) to function as a single DER. It also has the inherent capacity to include the influence of the system on the aggregated DER output. Many projects have been done using HPP concepts, for example, the European virtual fuel cell power plant [3], and the FENIX HPP [4].

In order to participate in the electricity market, the HPPs may have nondispatchable and dispatchable power plants including renewable and non-renewable ones, storage units such as batteries and pump storage, and responsive loads that have some flexibility in their energy consumption levels. In other words, in HPPs, there are diverse kinds of power plants and storage units combined to overcome and handle the stochastic nature of renewable generators, the energy price and so on in a coordinating attitude [2]. HPP consists of two categories, the commercial HPP (CHPP) and Technical HPP (THPP). Fundamental and most essential functions of CHPP are to optimize and schedule the production of aggregated DER units and consumption of the aggregated Demand Response (DR) resources. These functions are generally based on submitting DERs' characteristics, predicting the production and energy consumption, forming offers or bids, submitting bids or offers to different electricity markets, calculating optimal production and consumption, and making a daily schedule, etc. On the other hand, the THPP, which is defined comprehensively in [5], takes into consideration the actual system impact on the DER aggregated profile in addition to the cost and operating characteristics of the portfolio. The THPP is composed of DERs which are located at the same geographical site. The most important tasks of the THPP are uninterrupted monitoring, managing of financial issues, fault detection and localization, and so on [6].

1.2 Research Objectives and Scope

The aims and scopes of this thesis are as follows:

- A coordinated strategy of an HPP, which includes different types and configurations of aggregators, will be identified to participate in electricity markets.
- Novel bidding strategies will be found to maximize the profit of different possible configurations of HPP.
- Bidding strategies of an HPP consisting of a WPA and a CAES aggregator will be proposed for the participation in three electricity markets (day-ahead, intraday, and balancing markets).

- An optimal offering strategy model for the joint operation of a WPA and a DRA as an HPP will be developed to maximize their expected profit and also to mitigate uncertainties related to stochastic nature and wind power outage.
- HPP will be optimally managed to improve market profit, congestion management, and voltage stability considering network constraints.

1.3 Dataset

In this thesis, the preliminary intention was to utilize the data of the Australian electricity market. Unfortunately, due to the simple structure of the Australian electricity market, a proper alternative dataset from Spain electricity market, which has been used in numerous studies, was carefully chosen for the analysis and simulation. Spain electricity market includes deferent types of electricity markets, namely, DA, intraday, and balancing markets. In addition to market electricity prices, the data related to wind and costumers are also taken from Spain to be consistent.

1.4 Contributions and Organization of the Thesis

1.4.1 Intellectual contributions

The key contributions of this these can be summarized as follows:

- A CAES aggregator equipped with a simple cycle mode operation is modeled, where this aggregator has the ability to work as a gas turbine and is correlated with a WPA as an HPP to participate in electricity markets. In the proposed approach, the WPA uses the CAES to tackle its stochastic input and uncertainties related to different electricity market prices, and CAES can also use WPA to manage its charging/discharging and simple cycle modes more economically. A three-stage stochastic decision-making method is used to model the mentioned optimization problem which considers three electricity markets, including DA, intraday, and balancing markets. The problem is formulated as mixed-integer linear programming which can be solved with available commercial solvers. Also, CVaR is added to the problem to control the financial risk of the problem and offer different operation strategies for different financial risk levels. The proposed method can provide both bidding quantity and bidding curves to be submitted to the electricity markets which is tested on a realistic case study based on a wind farm and electricity market located in Spain.

- The stochastic nature of wind power generators and their possible outage are crucial issues which make them challenging to participate in electricity markets. However, demand-side as a decent balancing resource can be used to compensate for the challenges of supply-demand balance or state of outage for wind generators. In the next study, firstly the outage of wind generators is modeled. Then, an offering strategy with three-stage stochastic programming is presented for an HPP which includes a wind power producer and a demand response provider. Three electricity markets are also considered in this study, including DA, intraday, and balancing the market. The CVaR is also added to the offering strategy to control the profit risk. The offering strategy is tested in a wind farm and electricity market located in Spain.
- In the final study, an HPP including a CAES aggregator with a WPA is modeled considering network constraints. Three objective functions are considered, including

electricity market maximization, congestion management, and voltage stability improvement. In order to properly model the WPA, pitch control curtailment wind power level is added to wind generators. Multi-objective Pareto front solutions are considered to properly optimize all the mentioned objective functions, and finally, the best solution is provided using the fuzzy method. The proposed approach is tested on a realistic case study based on a wind farm and electricity market located in Spain, and IEEE 57 bus test system is used to analyze the network constraint effects on the HPP scheduling for different objective functions.

1.4.2 Thesis organization

The rest of the thesis is organized as follows. Chapter 2 reviews the background, literature, and the concepts of different types of HPP, their operating systems, electricity markets, and stochastic programming. Chapter 3 studies a risk-constrained bidding strategy for the joint operation of wind power and compressed air energy storage aggregators. A risk-constrained demand response and wind energy systems integration are investigated to handle stochastic nature and wind power outage in Chapter 4. A bidding strategy of HPP considering network constraints is proposed in Chapter 5 for voltage stability improvement, electricity market profit maximization and congestion management. Finally, Chapter 6 concludes the thesis along with suggestions for future works.

2 Background and Literature Review

This chapter reviews the background, literature, and the concepts and different types of HPP, along with the corresponding HPP operating. Furthermore, it briefly summarizes the organization and agents involved in electricity markets. The fundamentals of stochastic programming are also provided.

2.1 HPP Components

There is some substantial literature that studied HPP problems such as the modeling of DERs, storage units, and other related components in an HPP. In what follows, the HPP components are firstly described, and then the most critical literature related to them is briefly introduced.

An HPP usually has three active components. The first component consists of the conventional dispatchable power plants, which are usually small scale fossil fuel power stations, and intermittent generating units. The second component may include the storage units which store electrical energy at a specified time in order to use it in the future. The third component comprises responsive or flexible loads, which covers residential and industrial electrical energy systems.

Different components and strategies are used in literature for HPPs; for example in [7], the HPP system consists of wind, solar, hydrogen and thermal units. In this study, the intermittent resources of the HPP are the wind and solar generating station units. Ref. [8] considers an HPP consisting of DGs, electric vehicles and capacitors. Ref. [9] studies an HPP which is equipped with intermittent and conventional power plants including renewable sources and storage units. In [10], an HPP which includes wind generation units as an intermittent source pumps storage system as a storage facility, and a conventional dispatchable power plant is scheduled. Ref. [11] studies the typical HPP configuration and establishes an HPP with small generators including the wind, solar, CHP plants and flexible loads. In [12], an HPP, including solar units and responsive demands, is explored. Ref. [13] studies a CHPP which includes DERs, battery storage units, and flexible loads. Ref. [14] considers an HPP as the combination of wind power units along with electric vehicles. Ref. [15] suggests a procedure to create an HPP, including a wind generator and a DR provider. An HPP with wind generation units and pumped storage unit station working in a remote and isolated island is studied in [16].

In the following subsections, different components of HPP are defined in detail, and the related recent literature is briefly described.

2.1.1 Energy Production Units

Gas turbines, diesel generators, and biodiesel or biogas resource-based generators are some of the examples of conventional dispatchable power plants that are used in an HPP.

Nowadays, renewable energy resources are an essential part of an HPP. These kinds of energy resources are intermittent and have stochastic inputs. In other words, their output comes from energy sources that generally depend on natural resources such as the wind or sunlight. As a consequence of the mentioned phenomena, the output of these kinds of stochastic generating units is naturally hard to predict. Besides, these stochastic generating units are nondispatchable. Therefore, they need to be provided with backup units such as conventional dispatchable power plants and storage units.

Besides, using an electrical generating station for providing electricity and heat together as CHP units are also very attractive and popular in an HPP. The CHP concept, in particular, has the best thermal efficiency. Also, in the direction of adjusting for the imbalance and likely financial disadvantages, the CHP is used to prevent the system from financial risks. For example, in [17], the capability of an HPP that includes CHP and solar units facilities is assessed to reduce the imbalance between the power generation and consumption due to the renewable generations. In this study, the HPP is willing to make energy bids into the markets, including the day-ahead (DA) and balancing markets. The balancing market alleviates the energy imbalance due to the difference between the expected value of the predicted electricity and the actual output. The CHP is used for adjusting this imbalance.

Different control methods and the procedure can be used for CHP-based HPPs. For example, a decentralized control method is explored in [18] for optimizing the residential systems including CHPs, heating boilers and thermal storage. In [18, 19], the most desirable procedure of CHP arrangements is characterized. Ref. [20] demonstrates a system to assess the most desirable bidding planning of an HPP consisting of a CHP coupled with district heating (CHP–DH). In this paper, the ultimate goal is to investigate a bidding strategy for an HPP with maximum benefits. In [21], a stochastic profit-based model is taken into consideration for an industrial customer with CHP units in which the consumer requirements are provided by a responsive load.

A modeling methodology for CHP systems is presented in [22] as an element of the HPP with a high penetration of renewable energy resources. The operational schemes of CHP systems are demonstrated in connection with the market.

2.1.2 Storage Units

Storage units provide an opportunity for an HPP to transfer electrical energy from one period to another. The most important purpose of using storage units is to utilize this energy at a future time. Nowadays, in the production systems where stochastic renewable generators are used, the storage units are taken into consideration to balance the demand and generation. Ref. [23] reviews the storage units technologies used with stochastic renewable generators.

Many types of storage units can be used in modern HPP. The most important storage units that can be combined with the HPP are Hydraulic Pumped Energy Storage (HPES), which is a sort of hydroelectric energy storage used for balancing load; Compressed Air Energy Storage (CAES), which is one way to store energy using compressed air; Flywheel Energy Storage (FES), which works by speeding up a rotor to an exceedingly high speed and preserving the produced energy for use at another time; Superconducting Magnetic Energy Storage (SMES) systems, which accumulate energy in the magnetic field generated by the flow of direct current in a superconducting coil; Electric double-layer capacitors (EDLC); Battery Energy Storage System (BESS); and so on. Ref. [24] reviews the HPES capabilities, technical progress, and hybrid systems that include wind-hydro, PV-hydro, and wind-PV-hydro.

Also, electric vehicles, including both Plug-in Electric Vehicles (PEVs) and Plug-in Hybrid Electric Vehicles (PHEVs) can be considered as energy storage units in HPPs. For example, in [14], an HPP considered as the combination of wind power units and electric vehicles. In this study, wind units try to use electric vehicles as a reserve storage unit to handle the uncertain nature of wind generators. Taking advantage of the rapidly growing number of electric vehicles, this study confirms that there is no need for preliminary investment in storage systems. A novel technique for backing up the scheduling of an HPP is suggested in [25]. The purpose of this technique is to reduce operation costs by considering the extensive integration of Vehicle-to-Grid (V2G). Ref. [26] evaluates the opportunities of using electric vehicles as energy storage units in an HPP. The effects of market procedures on the behavior of market performers and the owners of electric vehicles are simulated in [27]. Ref. [28] presents a review of electric vehicles used in a smart grid. Also, the challenges and problems caused by the large numbers of electric vehicles and investigation of their abilities to interact with the RESs and DR programs are reviewed in [29].

The investment cost and efficiency associated with the energy storage systems are important parameters affecting the planning and operation programs in power systems [133]. The efficiency and investment cost for a different type of energy storage systems are illustrated in Fig. 2.1. According to this figure, the CAES investment cost is less than the other large-scale types of energy storage systems. The efficiency of large-scale CAES is close to 70%, and owing to the low investment cost, this efficiency level is fair. Also, lifetime is one of the important parameters of energy storages. Fig. 2.2 depicts the lifetime and size range of different types of energy storages. According to this figure, the CAES systems have a long life duration in comparison with many other types of energy storage systems which are capable of being employed in power systems to integrate with renewable energy resources. Other features such as penetration in power systems and applications for different types of energy storages are tabulated in Table 2.1. According to this table, the hydro pumps have the most penetration level in power systems while their applications are less than some energy storage technologies such as CAES, secondary batteries, and flow batteries.

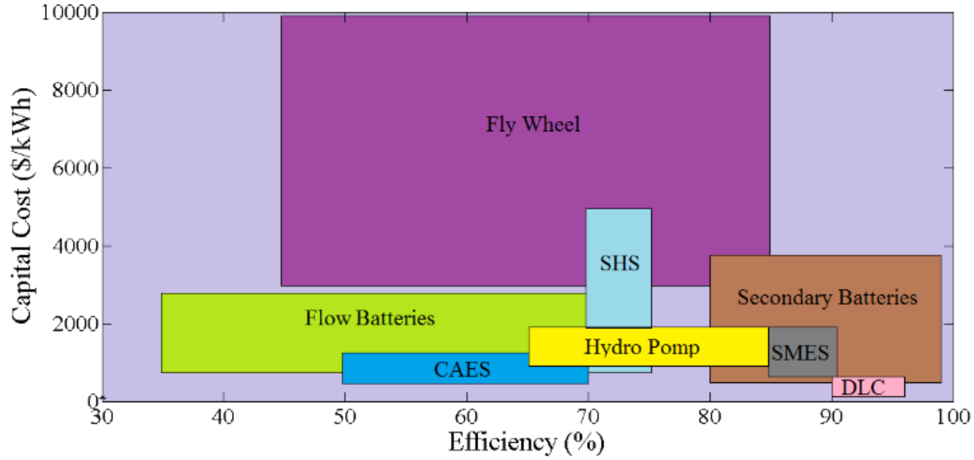


Fig. 2.1 Comparison of the efficiency and investment cost for different type of energy storage systems

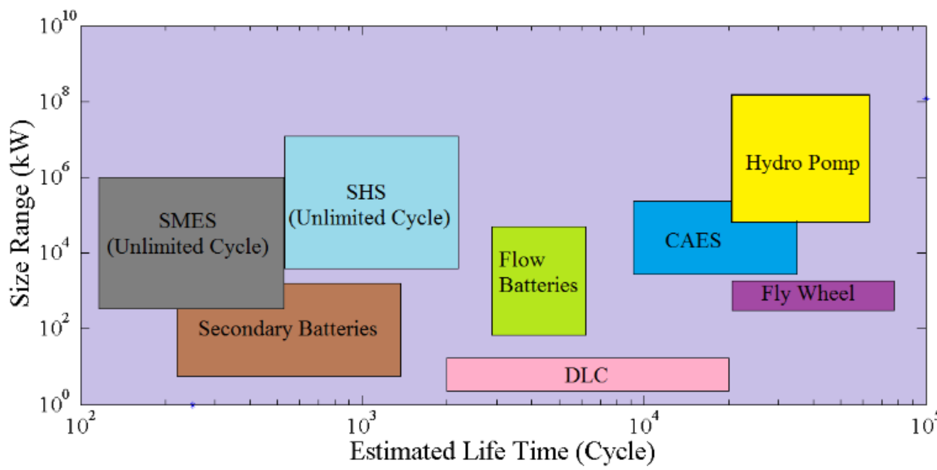


Fig. 2.2 Comparison of the life time and size range of different types of energy storages

Table 2.1 Comparison of different energy storage systems

Technology	Penetration	Applications
Hydro Pump	3%	Electricity, Load Leveling
CAES	< 1%	Integration with Renewables, Power Quality, Spinning Reserve, Electricity, Peak Shaving, Transmission and Distribution (T&D) Applications
Fly Wheel	< 1%	Electricity, Power Quality
Secondary Batteries	< 1%	Integration with Renewables, Power Quality, Spinning Reserve, Electricity, Peak Shaving, T&D Applications
Flow Batteries	< 1%	Integration with Renewables, Power Quality, Spinning Reserve, Electricity, Peak Shaving, T&D Applications
Double-layer Capacitor (DLC)	< 1%	Power Quality, Deployed in Uninterruptable Power Supplies
Superconducting Energy Storage (SMES)	< 1%	Electricity, Power Quality
Sensible Heat Storage (SHS)	< 1%	Electricity, Power Quality, T&D Applications

2.1.3 Flexible Loads

Flexible loads refer to the loads that can adjust their typical consumption patterns in response to variations in the electricity price, or to incentive payments [30]. The flexible or so-called responsive loads are composed of two parts. The first part is a structure which is used for communication between the load and central section. The second part is a control system necessary to regulate the flexible loads' utilization level. The flexible loads' utilization level in an HPP can be changed to meet certain requirements. These changes can be done through an authorized control command or a kind of price signals called dynamic pricing methods. DR can mitigate the critical load periods and improve the reliability of the system. However, implementing the DR needs an accurate demand forecast. The inaccurate forecast of demand is the main uncertainty in a system equipped with DR programs.

Practical limits constrain the flexibility of dispatchable power plants and intermittent generating units. Therefore, the flexibility of the system is restricted if only energy production units are used [31, 32]. DR can be used to increase the flexibility of the system. An assessment of the DR flexibility of housing smart appliances is presented in [33]. Ref. [32] declares a comprehensive plan and model of DR and responsive loads. In this study, the flexibility of responsive loads is exploited using price-responsive shiftable demand bids in the energy market along with spinning reserve bids in the reserve market.

Different DR definition and categorization are considered through the Federal Energy Regulatory Commission (FERC). The state-of-the-art DR definition and categorization are presented thoroughly in [34]. In this study, a comprehensive advantage of DR, along with the impacts of DR on electricity prices, is considered.

DR needs to be incorporated in a system like an HPP to participate in an electricity market. Ref. [35] assesses the action of incorporating a DR into an HPP trading in a DA market and a balancing market. In [36], a functioning process with novel DR programs for HPP to take part in an energy market is suggested. Also, a method to gain the best offering strategy for an HPP consisting of a WPA and a DR in electricity markets is proposed in [15].

The high penetration of both DERs and DR in HPPs requires state-of-the-art technologies for preserving system reliability. The problems caused by high penetration of DERs are reviewed in [37]. Ref. [38] reviews the current application and operation strategy of DR in a smart grid. Ref. [39] presents a review of integrating the DERs and DR in electricity markets.

A new DR strategy is offered in [40] which is based on the consumers' submissions of candidate load profiles. Thus, forecasting the price elasticity of demand is not needed. Furthermore, the suggested DR strategy is improved and employed in a framework of the HPP.

2.2 Operation Systems of HPP

The HPP organizes the dispatchable power plants, intermittent generating units, storage units, and DRs using an Energy management system (EMS). EMS manages the energy transactions in the HPP through bidirectional communication. It controls all the units, including the non-dispatchable and dispatchable power plants, storage units along with responsive loads [6, 41]. The EMS has the capability of controlling the system for many different objectives, such as minimizing costs, minimizing the output pollution, or maximizing the profits. With the aim of these objectives, the EMS is required to receive data related to the units and predict the stochastic information such as renewable generators inputs, the price of energy, probable bottlenecks in the grid, etc.

In many existing studies, the modeling of uncertainties is also taken into account, such as the uncertainties in non-dispatchable renewable recourses, as well as the uncertainties in linear and nonlinear optimization problems. To handle the uncertainty problem, the energy production units, storage units, and DRs should be coordinated by the EMS of HPP to guarantee the stability of the HPP. In [42], the energy and reserve are organized at the same time in an HPP, and the Point Estimate Method (PEM) is used for modeling the uncertainties. Ref. [43] offers a stochastic programming model for involving the joint activity of the wind farm hydro system. In this study, in order to effectively handle the prediction error of wind power generation, the HPP owner considers its hydro plants as reserve capacity. The problem is also formulated as a Mixed Integer Linear Programming (MILP) to be solved by available commercial optimization programs. In [44], a probabilistic approach based on PEM is used in an HPP. In this study, the uncertainty of DERs is compensated by the additional reserves. The large-scale integration of DERs is considered thoroughly by industrialized economic dispatch algorithm. Ref. [14] considers an HPP with wind power units and electric vehicles. In this study, wind units use electric vehicles as a storage unit to handle the uncertain nature of wind generators. In [12], systematic control of an HPP, including solar units and responsive demands, is explored to handle the uncertain nature of solar generators. The purpose of this study is to propose a flexible load which can be changed in a wide range. In order to do so, the power output of the solar units and responsive demands are synchronized. This problem is formulated as a Mixed Integer Programming (MIP) problem. A trading model based on the stochastic programming to maximize the HPP bidding profits in the DA market and balancing market is presented in [45]. The trading model considers the uncertainty of stochastic variables of the HPP. In the direction of moderating the uncertain effects of wind and solar units in an HPP, a robust optimization is presented in [46] to produce a stochastic model considering DR. In [47], a stochastic approach is offered for HPPs considering diverse uncertainties in generation units, electricity consumption, and price. The stochastic approach allows them to participate in a DA market. Ref. [48] deliberates the firm capacity provision under an HPP prototype in which the stochastic and intermittent nature of renewable sources is provided. In this study, the decision trees are used in this stochastic optimization problem considering the short-term and long-term firm capacity provision periods. This prototype makes it possible for the

HPP to make available reserve capacity and contribute efficiently in electricity markets. Ref. [49] proposes a distributed optimization algorithm for the HPP bi-level optimal dispatch considering the uncertain number of agents. An HPP model is presented in [50] to expand a heuristic dynamic game theory considering the price uncertainty in addition to the security constraint. The proposed model can efficiently simulate the actions of market performers in a given amount of time to evaluate the economic behavior of the performers.

The bidding strategies offered by an HPP can be organized to fulfill different objectives. For example, in [2, 51], the bidding problem faced by an HPP is presented with two objectives, participating in DA markets and providing spinning reserve service. The proposed bidding strategy is a non-equilibrium model based on the deterministic price-based unit commitment (PBUC). The bidding strategy takes into account the supply-demand balancing constraint and security constraint. The objectives of [11] are to maximize the self-supply and market revenue of the CHP-based HPP from the perspective of the HPP in addition to the system operators. Ref. [52] suggests a procedure based on an evolutionary optimization algorithm in order to minimize the operational cost of an HPP, which is in charge of DERs in a distribution network. The goal of Ref. [53] is to determine a two-stage operational planning structure for the short-term operation of the HPP. In this study, a stochastic bidding model is suggested for the HPP to maximize the profit from the energy market. Ref. [20] presents a method to find the optimal bidding planning of an HPP comprising a CHP and RES system for the maximum benefit. Ref. [13] studies the optimal bidding approach for a CHPP, which includes DERs, battery storage units, and flexible loads. The proposed optimal bidding method is used to maximize the profit along with the expected real-time production and the consumption minimization. In [54], a model of THPP is proposed to reduce its cost with non-linear programming considering the constraints of DGs, distribution systems and DR. One of the most important objectives that can be considered in an HPP is the system emission reduction. A multi-agent system is designed in [55] for the emission regulation of the aggregated micro-generators. In this study, the simulations of the operational system are confirmed by using an experimental system. The emissions of HPP are regulated to be close to the reference value. In [56], an EMS model for HPPs is proposed to investigate the cost and emission impacts of HPP formation and PHEV penetration for a case study in California.

An arbitrage strategy can be used for HPPs taking part in energy and ancillary service such as spinning reserve and reactive power services markets [57]. In [58], the aggregation of DERs as an HPP is studied in a distribution network to allow it to take part in joint energy and reserve markets economically. This approach, which is predicated upon the price-based unit commitment method, has considered virtually all the technical data in the proposed model. Ref. [59] develops an HPP to economically offer conventional energy storage systems through the existing network assets along with flexible demands. The cost-effective benefits of the HPP for frequency response services were assessed. In [60], energy and ancillary services are offered to solve the joint management for the following day in view of minimizing the HPP total operation costs. In [61], a probabilistic model is proposed and investigated for optimal DA scheduling of electrical and thermal energy resources in an HPP by simultaneously scheduling the energy and reserve in the presence of energy storage devices and demand response resources.

2.2.1 Co-operation of WPA and DRP

Due to the stochastic, unstable and non-dispatchable nature of wind generations and their possible outage, it is usually challenging for these kinds of producers to take part in electricity markets and compete with other producers such as conventional power plants. Accordingly, it is vital to propose a new strategy for WPAs to assist them in tackling these problems [62].

Recently, using demand response programs as a rapid resource generator has been growing fast for different purposes [63, 64]. The ability to rapidly respond makes demand response resources a flexible resource to manage the unstable nature or even possible outage of wind power generators [65, 66].

Many studies provide an offering strategy for WPAs to participate in electricity markets [67-69]. For example, Ref. [70] offers a procedure to develop an offering strategy for a WPA including different types of electricity markets and considering the uncertainty related to the stochastic nature of wind and prices of different markets. Ref. [71] recommends an offering strategy by considering a WPA as a price-maker in the DA market. In this paper, the uncertainties related to the stochastic nature of wind and prices of different markets are also considered. Ref. [72] studies an offering strategy of a WPA as a price-taker in the DA market and a price-maker in the balancing market. Ref. [73] considers two different offering strategies for the cooperative contribution of a wind power generator in two electricity markets, including energy and primary reserve markets.

Also, some studies provide offering strategies for WPAs, along with other producers [74-76]. For example, Ref. [77] studies the joint operation of a WPA and a pumped-storage facility by considering the uncertainty related to the stochastic nature of wind and market prices. The impact of the stochastic nature of wind on the amount of pumped-hydro stored energy in a future U.K. system is evaluated in [78]. Ref. [79] offers a bidding strategy for a WPA and hydro facility to be able to participate in a DA market using the CVaR model to control the financial risk. Ref. [80] evaluates two models including a WPA supported with a gas turbine and a WPA supported with a CAES.

Recently, many studies offer demand response resources as a more flexible resource to manage the unstable nature of wind power generators [81-83]. For example, Ref. [84] specifies the optimized value of load as a demand response for congestion management and the improved use of wind power generations. An offering strategy for a WPA and a flexible load which can cover the wind power imbalances is suggested in [85] for participation in a DA electricity market. In order to minimize the total operational cost including imbalance fines because of wind energy over- and under-commitments, optimal scheduling of critical peak pricing events is evaluated in [86] from the perspective of a demand response facility. Ref. [87] offers a new offering strategy for a WPA to participate in three electricity markets including DA, intraday and balancing markets with the help of a demand response resource which is allowed to contribute to the intraday market. Ref. [88] offers a novel method that considers the uncertainty related to the amount of wind power generation and the load for corrective voltage control under contingencies.

2.2.2 Co-operation of Commercial CAES Aggregator and WPA

Nowadays, there is extensive attention towards energy storage systems primarily commercial CAES which is a developed energy storage system with the capability of functioning as a gas turbine when there is no air in the reservoir [89]. Commercial CAES facilities can provide energy-shifting when there is instability in the electricity price. Besides, it is important to notice that the ability to work as a gas turbine (simple cycle mode operation) makes the CAES facilities different from other kinds of energy storages because they can follow their daily schedule in a more optimized approach and exploit price spikes when the reservoir is entirely depleted [90].

To this end, several studies concentrate on best self-scheduling strategies for CAES facilities and calculate their energy arbitrage income in diverse electricity markets [91]. For example, a co-optimized CAES dispatch model to illustrate the significance of providing operating reserves and energy arbitrage in different U.S. electricity markets is presented in [78]. Ref. [90] proposes a risk-constrained bidding strategy for a commercial CAES plant that contributes to the DA energy market.

Many studies provide an offering strategy for WPAs to participate in electricity markets. In [70], a procedure is proposed to develop an offering strategy for a WPA including different types of electricity markets and considering the uncertainty related to the stochastic nature of wind and prices of different markets. Ref. [71] recommends an offering strategy by considering a WPA as a price-maker in the DA market. Ref. [72] studies an offering strategy of a WPA as a price-taker in the DA market and a price-maker in the balancing market. Ref. [88] presents a novel method considering the uncertainty related to the amount of wind power generation and load for corrective voltage control to cope with the states in which the power systems experience voltage instability due to severe contingencies.

Some studies provide offering strategies for WPAs, along with other producers [92]. In this regard, Ref. [77] studies the joint operation of a WPA and a pumped-storage unit by considering the uncertainty related to the fluctuating nature of wind and prices of the market.

The impact of wind uncertainty on the amount of pumped-hydro stored energy in the future U.K. system is evaluated in [78]. Ref. [79] proposes a bidding strategy for a WPA and hydro facility to be able to participate in a DA market using CVaR model to control the financial risk. Ref. [80] evaluates two models, including a WPA supported with gas turbines, and WPA supported with a CAES. An offering strategy for a WPA and a flexible load which can cover the wind power imbalances is suggested in [85] for participation in a DA electricity market. In order to minimize the total operational cost including imbalance fines because of wind energy over/under-commitments, an optimal scheduling of critical peak pricing events is evaluated in [86] from the perspective of a demand response unit which has wind energy to be able to trade in the DA market properly. Ref. [87] presents a new offering strategy for a WPA to participate in three electricity markets including DA, intraday and balancing markets with the help of a demand response resource which is allowed to contribute to the intraday market.

2.3 Types of HPP

The HPP is generally classified into two categories, which include technical and commercial ones. The most important tasks of the Technical HPP (THPP) are uninterrupted and indefinitely long monitoring, managing of financial issues, fault detection and placement, and so on. Also, the most significant responsibilities of a Commercial HPP (CHPP) are the activity of protecting and submitting of DERs' characteristic, predicting the amount of consuming and producing energy, and so forth. Furthermore, these two types of HPP are described in more detail in the following:

2.3.1 Technical HPP (THPP)

The THPP is composed of DERs which are located at the same geographical site, and also includes the simultaneous effect on the upstream network in addition to demonstrating the price and operational features of the portfolio. Amenities and roles that are performed by most THPPs are organizing the Distribution System Operator (DSO), along with making a possibility for Transmission System Operator (TSO) as well as ancillary services [4, 6].

In THPP, small-scale units can have ancillary services and decrease unattainability possibilities through varying portfolios in comparison with individual and independent units. The technical abilities of DGs and their ancillary services potentials are comprehensively considered in [93, 94]. DSOs that are exploiting the THPP conception can be treated in place of Active Distribution Network (ADN) agents [41] which can also utilize ancillary services presented by DERs to enhance the operational performance of the network.

Some of the essential capabilities of THPP are constant situation monitoring, benefits managing which is reinforced through statistic records information, self- recognition of the system modules, fault placement, easier maintenance services, and numerical investigation during task optimization [6].

2.3.2 Commercial HPP (CHPP)

A CHPP has an accumulated profile which denotes the price and operational features of the DER portfolio. It is vital to mention that the influence of the upstream distribution network is not carefully contemplated in the accumulated profile of this kind of HPP. Facilities in a CHPP trade in different electricity markets including DA, intraday and balancing markets.

CHPP is a kind of speculator who trades aggressively in electricity markets and makes DER units having the opportunity to provide a clear, unobstructed view in the energy markets[6]. By using these benefits of CHPP for DER units, they can gain access to electricity markets, which in particular decreases the exposure to a chance of losing benefits. The DER units that are under the control of a CHPP can be spread out or scattered in all over the distribution networks or even throughout transmission networks.

CHPP can schedule the production of the aggregated DER units to coordinate with the aggregated Demand Response Resources (DRRs). In general, the actions and activities expected from a CHPP include the generation of DER, prediction of energy consumption, supervision of possible demand outage, forming offers or bids, submitting bids and offers to electricity markets, calculating optimal production and consumption and making an everyday schedule.

2.4 Electricity Markets

This section provides a summary of the organization and agents involving in electricity markets. The purpose of this section is also to provide the fundamental structure needed to know about the scholastic programming problems addressed in different chapters of this thesis. More information about electricity markets is available in [95-100].

2.4.1 Organization and Agents

In the last two decades, the power generation and consumption system have mostly developed from a central functioning form to a competitive one in the world. This process has begun in the US by the Federal Energy Regulatory Commission who legislated a charter to raise competitiveness in the electricity markets in 1996 [101]. Also, at the same time, the European Union-sponsored Directive designed at the liberalization of buying of energy by eligible users to start the fundamental instructions for European electricity markets [102].

The new electricity markets competitive form has anticipated to raise the effectiveness of power systems while assuring a satisfactory quality of the electricity production and attaining the least possible price for consumers.

1) Market Organization

In the most electricity markets in the world, there are typically some trading arenas to let the electricity producers and consumers do their energy transactions which are categorized into pools (DA, intraday and balancing markets) and futures markets. Note that pools are electricity markets with short-term (commonly within a day) trading systems which mostly cover the more significant part of energy transactions. The DA and intraday markets are very similar, except, intraday markets are done later and after the DA market. Similarly, the balancing market provides short-term (commonly within an hour or half an hour) trading systems usually helping non-dispatchable renewable power plants such as wind or solar power producers to compensate for their lack of production or sell their excess production. In contrast, the futures market provides long-term (commonly within a week to a year) trading systems.

There are some other types of electricity markets, namely reserve (spinning and non-spinning) and regulation (automatic generation control, AGC) markets that are usually used to guarantee a safe and balance energy trading.

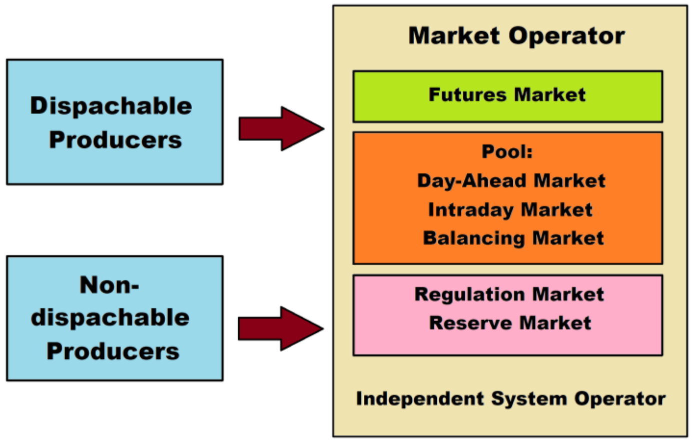


Fig. 2.3 electricity markets trading framework with producers: dispatchable and non-dispatchable producers

Fig. 2.3 shows the electricity markets trading framework, including the futures market, pool, reserve, and regulation markets with producers including dispatchable and non-dispatchable producers. In general, market operator clears DA, intraday, balancing and futures markets, and the independent system operator clears the other markets.

2) Agents

Agents contributing to the futures market, pool, reserve, and regulation markets are briefly defined as follows:

- Consumers: consumers are the buyers of the electricity who possibly buy electricity in the electricity markets such as the futures market and pool targeting for the minimization of their cost. Also, consumers sometimes contribute to the reserve market as a demand response provider by changing their consumption to get more benefits.
- Retailers: a retailer delivers energy to the end-users that do not want to buy electricity from markets directly. Different from other producers, a retailer itself

usually has no power generation units to provide electricity to its customers. Retailers make the most of their profit by buying electricity as cheap as possible. They sell electricity to their clients at minimum prices because of the possibility of losing them to other retailers.

- Dispatchable Producers: a producer is an entity possessing some power generation units, including renewable generators or non-renewable ones. Producers sell their produced electricity markets such as the futures market and pool targeting for the maximization of their profit. Also, producers sometimes contribute to the reserve and regulation market to get more benefits.
- Non-dispatchable producers: Non-dispatchable energy producers such as wind and solar producers have the challenge to deal with the uncertainty and stochastic nature of their sources. They usually sell in the pool but need to contribute to the balancing market to buy for their deficient production or sell their excess of produced energy.

As it is seen in Fig. 2.3, there are two primary recognized electricity market agents: the independent system operator and the market operator, which are briefly discussed as follows:

- Market operator: Market operators are usually impartial agents in charge of the financial supervision and administration of the electricity markets. Moreover, the market decision-maker oversees the market instructions and procedures and decides on the energy quantities and its prices.
- Independent system operator: This operator is also an impartial agent responsible for the technical supervision parts and usually takes control of the regulation electricity market.

3) Pool

As is shown in Fig. 2.3, the pool is composed of three essential markets, including DA, intraday markets, which are shorter-term markets and balancing market and are well known as a real-time market.

Fig. 2.4 shows the pool and its procedures. As can be seen from Fig. 2.4, producers offer their energy production quantity and prices, and consumers and retailers bids their energy consumption quantity and prices. As shown in Fig. 2.3, and Fig. 2.4, there are three electricity markets, including the DA, adjustment, and balancing markets. As mentioned before and shown in Fig. 2.4, the market operator is in charge of clearing these three markets and finalizes the electricity quantities for each participant in the markets and price.

From the perspective of energy adjustment in the pool markets, the intraday market is usually cleared after DA market to adjust the imbalance energy while balancing markets are used to make last-minute adjustments. Therefore, non-dispatchable producers, such as wind or solar power plants based producers, usually tend to participate in markets such as intraday and balancing market when their forecasts of power production are more accurate. On the other hand, dispatchable producers, such as conventional power plants, tend to participate in the DA market, which has less financial risk among all electricity markets.

As can be seen in Fig. 2.4, producers, including dispatchable and non-dispatchable producers, offer their energy quantity and prices to the DA, intraday and balancing markets, while simultaneously retailers and consumers bid their energy quantity and prices. After energy bids and offers are collected, the market-clearing process is performed by the market operator, and its outcome is the final energy quantity and prices.

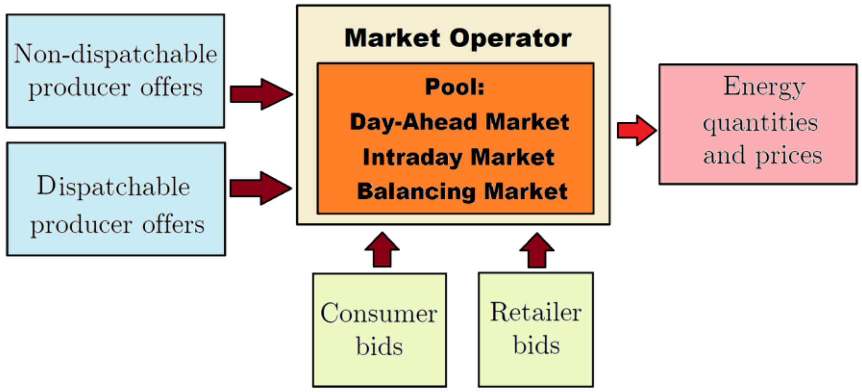


Fig. 2.4 pool and its procedures

The balancing market is an hourly based market which constitutes the energy trading for covering both the lack of energy production and excess of energy production. This market, which is also called real-time market, provides the latter market for energy trading to make a balance between the produced and consumed power. In this case, the energy producers, especially non-dispatchable producers such as wind power plants, participate in the balancing market to compensate for their lack or excess of energy production by submitting their offers or bids.

Fig. 2.5 shows the balancing market and its procedures. The producers, especially non-dispatchable producers and consumers, contribute to the balancing market to compensate for their productions and consumptions, respectively. Also, the outcomes of balancing the market are cleared by the market operator after analyzing the offers and bids of producers and consumers, as shown in Fig. 2.5.

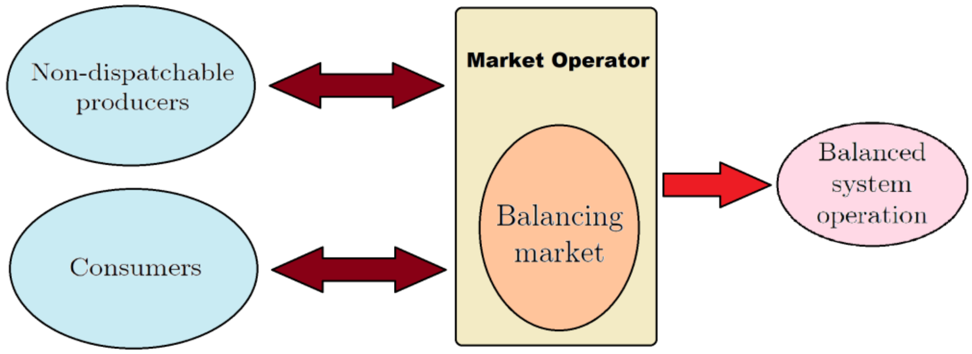


Fig. 2.5 the balancing market and its procedures

As a final point for pool electricity markets, it is essential to mention that in some electricity markets such as Australian electricity market, the period is shortened and is based on 30-minute periods [103, 104].

4) Futures Market

The main feature of prices of pool-based electricity markets (DA, intraday, and balancing markets) is high unpredictability, and this feature makes these electricity markets prices extremely uncertain. High volatility in the pool prices is not desirable due to its adverse effects on profits or costs anticipated by the producers and consumers contributing to these markets. On the contrary to the pool-based electricity markets, the futures market is a market which delivers electricity at fixed prices on a specified date in the future [105, 106].

Fig. 2.6 shows the futures market and its procedures. As can be seen in Fig. 2.6, there are generally two major types of products of futures markets (financial and physical), which include forward contracts and options. These two types of futures market have the time duration from one single week to possible few years, which let producers and users tackle and compensate the financial risk over the pool-based electricity markets.

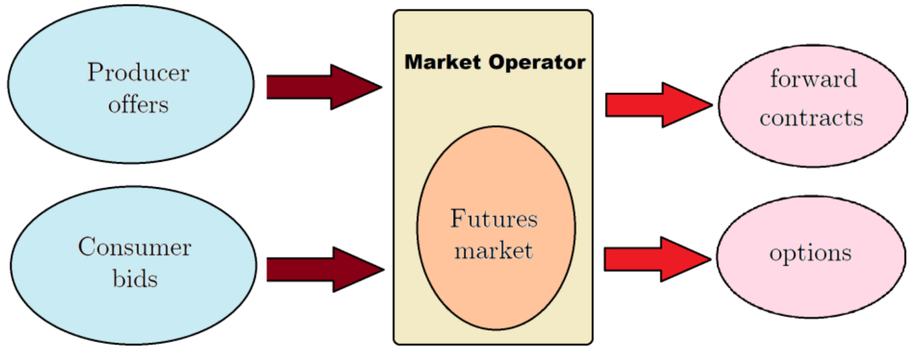


Fig. 2.6 the futures market and its procedures

The significant difference between a forward contract and an option is that in a forward contract, there is a contracted amount of energy to be delivered in a future at a fixed and contracted price, while in an option, there is a choice of a contracted amount of energy to be delivered in the future.

From Fig. 2.6, a producer might contribute to the futures market to sell its energy production at a deterministic price. On the other hand, consumers usually participate in this market to buy their required energy at a deterministic price. Finally, after analyzing the offers and bids of producers and consumers, the outcomes of the futures market is determined and cleared by the market operator, as shown in Fig. 2.6.

5) Ancillary Service Markets (Reserve and Regulation)

Electricity markets generally include three products: energy, reserve, and regulation. As discussed earlier, the energy market is the most essential and critical product. On the other hand, the reserve market is another significant product that provides secure energy when there are some failures in the equipment or uncertainties in the non-dispatchable producers. Fig. 2.7 shows the reserve market and its procedures. As can be seen from Fig. 2.7, the reserve market clearing process is usually performed by the independent system operator.

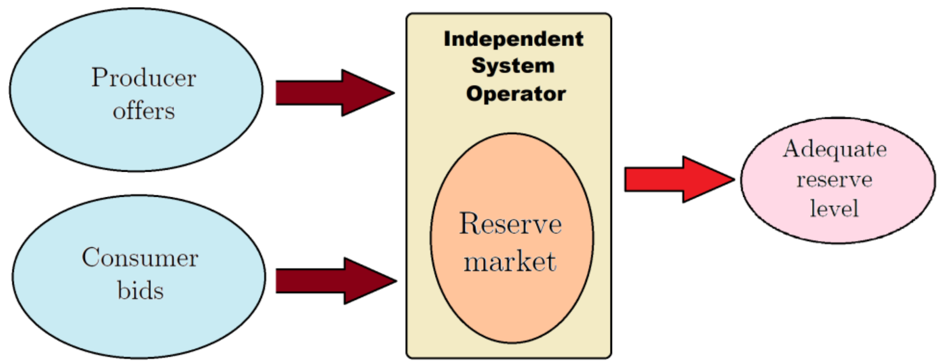


Fig. 2.7 the reserve market and its procedures

Typically, producers, especially dispatchable energy producers, offer energy to reserve market, but consumers (usually demand response providers) also deliver energy to reserve market by changing their consumption levels [107, 108]. After analyzing the offers and bids of producers and consumers, the adequate reserve level is determined by the independent system operator.

The regulation is also a significant product that guarantees that the frequency of the power system is kept within desirable values. Fig. 2.8 shows the regulation market and its procedures. As can be seen from Fig. 2.8, similar to reserve market, the regulation market clearing process is also completed by the independent system operator a couple of hours before the power delivery. Unlike the reserve market in which consumers could use provider reserve, in the regulation market, only producers, particularly dispatchable energy producers, offer energy to the market. As arrows indicate it in Fig. 2.7, after analyzing the offers of dispatchable producers, the adequate regulation level is cleared by the independent system operator.

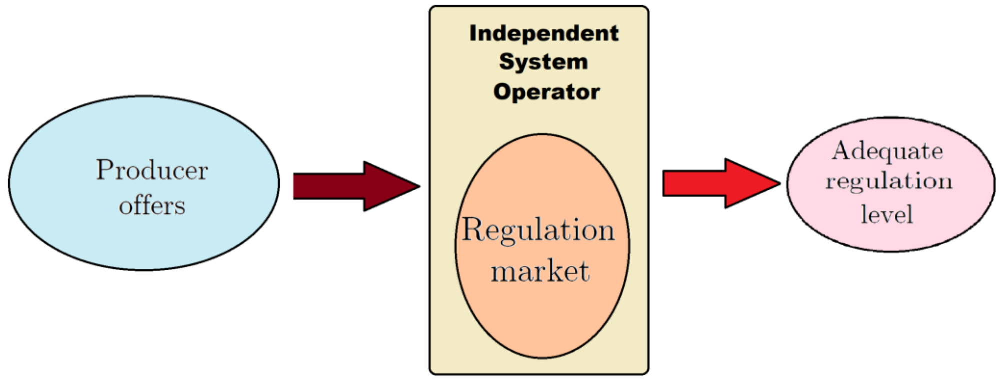


Fig. 2.8 the regulation market and its procedures

2.4.2 Decision Sequence and Uncertainty

1) Time Framework

In this subsection, the decision sequence of the different electricity markets, including the pool-based electricity markets (DA, intraday, and balancing), reserve, regulation, and futures markets, are discussed.

Fig. 2.9 shows the decision sequence of different markets, including the DA, intraday, reserve, regulation, and balancing markets. As can be seen from Fig. 2.9, the DA market is usually cleared before midday (12 pm) of the day d (today). After the clearance of DA market, intraday markets are generally cleared every couple of hours on both day d (today) and day d+1 (tomorrow). Also, after the clearance of DA market, reserve and regulation markets are normally cleared on day d. The balancing market is also cleared 10 to 15 minutes before each hour on day d+1 (tomorrow) as shown in Fig. 2.9.

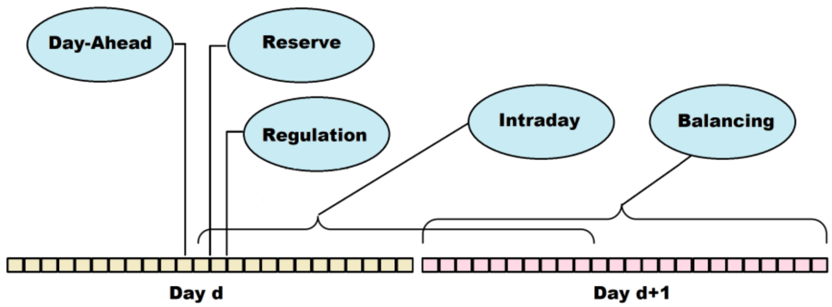


Fig. 2.9 the decision sequence of different markets

On the other hand, the futures markets, including forward contracts and options, provide energy for producers and consumers in any periods from at least one week to a couple of years [109, 110].

2) Uncertainty

As mentioned earlier in this chapter, due to the nature of electricity markets and intermittent energy resources, generally decision-making problems related to producers, users and decision-makers, such as offering in electricity markets and futures market trading are involved with uncertainties.

There are some methods for solving problems with uncertainties such as stochastic programming which offers a satisfactory framework to accurately formulate these types of problems [111]. Note that stochastic programming needs sufficient historical data for scenario generation, and if there is not much available historical data, some other types of methods such as robust optimization or information gap theory, can be used to solve the decision-making problems problem [112-115].

2.4.3 Decision Making

This thesis discusses decision-making problems within different planning frameworks for consumers, producers including intermittent and conventional ones and HPPs which coordinates different types of producers and consumers. The decision-making tools used in this thesis are briefly discussed as follows:

1) Consumer

Fig. 2.10 shows the diagram of different consumer decision-making problems with all possible electricity market participation [116]. As can be seen from Fig. 2.10, a consumer can participate in pool-based electricity markets including DA, intraday, and balancing markets, reserve market, and futures market. As it can be indicated from the arrows of Fig. 2.10, consumers prefer to buy through the futures, DA, intraday and balancing markets, and to sell electric power as a demand response provider [117, 118] to reserve market.

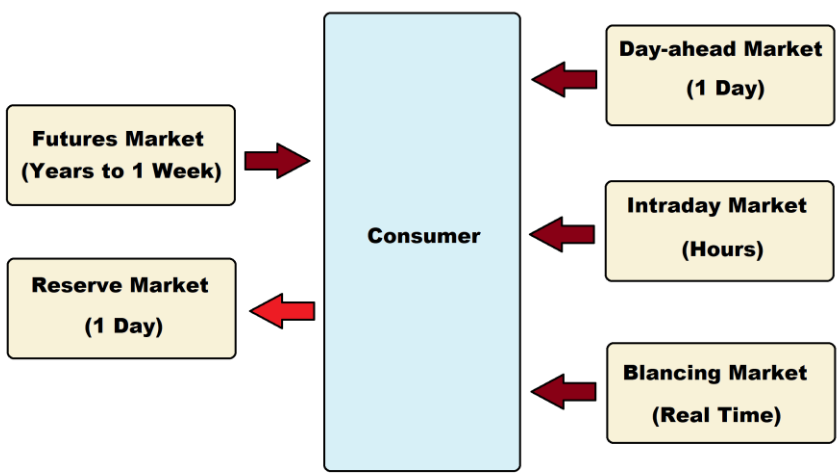


Fig. 2.10 Decision-making problem of consumer

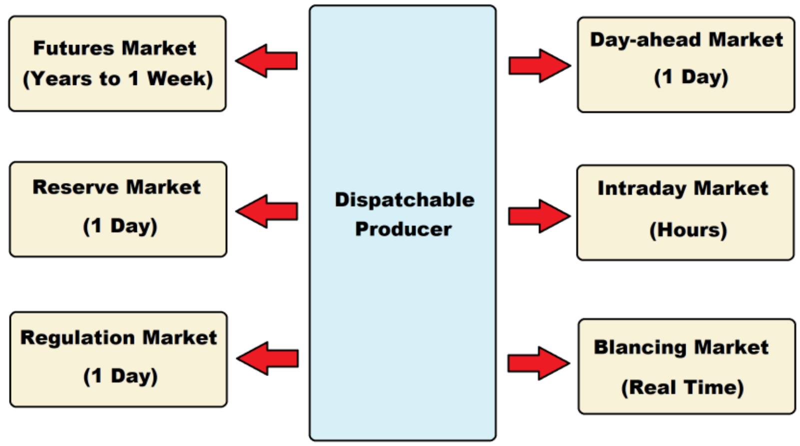


Fig. 2.11 Problems related to the dispatchable producer

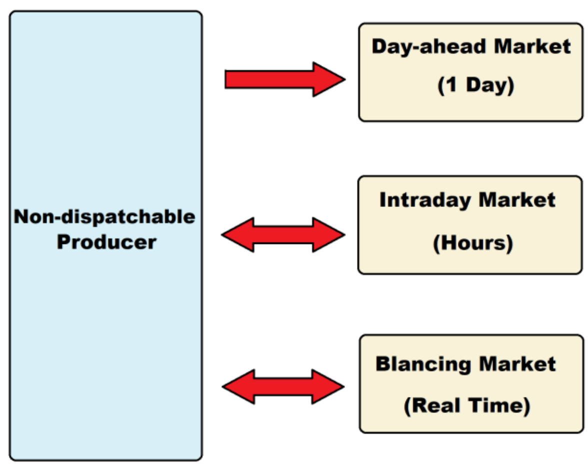


Fig. 2.12 Decision-making problem of the non-dispatchable producer

2) Dispatchable Producer

Fig. 2.11 shows the diagram of different dispatchable producer decision-making problems with all possible electricity market participation. As can be seen from Fig. 2.11, a dispatchable producer can contribute to reserve market, regulation market, futures market, and pool-based electricity markets, which include DA, intraday, and balancing markets. As it can be indicated from the arrows of Fig. 2.11, a dispatchable producer tends to sell energy to the futures, DA, intraday, balancing reserve, and regulation markets.

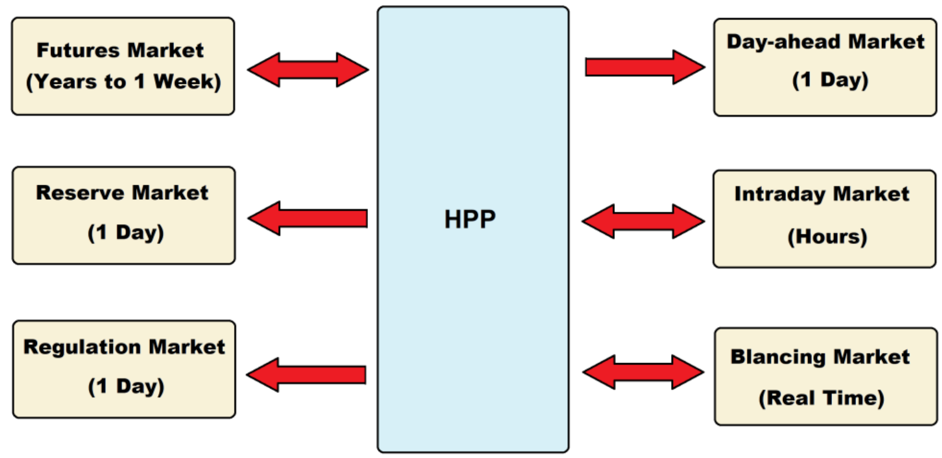


Fig. 2.13 Decision-making problem of an HPP

3) Non-dispatchable Producer

Fig. 2.12 shows the diagram of different non-dispatchable producer decision-making problems with all possible electricity market participation. As can be seen from Fig. 2.12, a dispatchable producer can contribute to pool-based electricity markets, including DA, intraday, and balancing markets. From the arrows of Fig. 2.12, a dispatchable producer is likely to sell electricity to the DA market, and buy/sell electricity to intraday and balancing markets. A non-dispatchable producer, such as solar or wind power plant based producers, needs to contribute to the balancing market to handle its stochastic power production as a result of its uncertain nature. These types of producers need to commonly contribute to the intraday market because of their closer power delivery time, which allows the non-dispatchable producer to predict more precisely its production.

4) Hybrid Power Plant

HPP has four significant producers. The first and the most crucial producer is the conventional dispatchable producer, which is usually small scale fossil fuel power stations. The second and another essential producer is the storage units which store electrical energy at a specified time in order to use it in the future. The third producer includes responsive or flexible loads, which encompass residential housing and industrial electrical energy. The last producer is non-dispatchable producer, which is composed of solar or wind power plant based producers.

Fig. 2.13 shows the diagram of different HPP decision-making problems with all possible electricity market participations. As can be seen from Fig. 2.13, an HPP can contribute to reserve market, regulation market, futures market, and pool-based electricity markets, which include DA, intraday, and balancing markets. As it can be indicated from the arrows of Fig. 2.13, an HPP is likely to sell electricity to the DA, reserve and regulation market, and buy/sell electricity from/to futures market, intraday and balancing markets.

2.5 Stochastic Programming Fundamentals

In real life, there are many decision-making problems with stochastic information and knowledge. The corresponding data shortage is usual in decision-making problems among different areas of study, including finances, engineering, economics, and in particular electricity decision-making problems such as electricity market problems. As a matter of fact, in electricity markets, decision-making problems and the corresponding stochastic information or uncertainties are usually prevalent. For instance, electricity prices and wind power generations are uncertain when a non-dispatchable wind power producer wants to participate in pool-based electricity markets such as DA and intraday markets. Also, electricity prices and consumption level are uncertain when a consumer wants to buy energy from electricity markets and sell to the markets as a demand response provider.

Nevertheless, even with stochastic information and knowledge, the electricity market decision-making problems must be solved, which encourages the electricity market agents to model their problems using stochastic programming.

Most problems, including electricity market decision-making problems, can be expressed as an optimization problem. The probability distribution of these optimization problem input data can be estimated by a group of probable sets with their related probabilities of occurrence. After the estimation and production of the scenarios and their associated probabilities of occurrence, the electricity market decision-making problems can be formulated as a stochastic optimization problem to attain a particular solution that can be the best solution for all scenarios. This specific solution is not the best solution for each single scenario, but it is the best solution if all of the scenarios with their related probabilities of occurrence are considered at the same time.

Due to the conversion of the stochastic input data to set scenarios, the subsequent objective function is a stochastic objective function and has to be categorized as a random variable.

This section of the thesis provides the fundamentals of stochastic programming. More information about stochastic programming problems are available in [111, 119-121], solution processes can be found in [122], and some useful tutorials are provided in [123, 124].

2.5.1 Random Variables and Stochastic Processes

Stochastic programming is one of the most common methods which is used to solve stochastic decision-making problems. In stochastic decision-making problems, there are usually some uncertain parameters; and random variables are normally used in stochastic programming to model decision-making problems with these types of parameters.

Random variables used in stochastic programming are commonly indicated by a limited number of scenarios [125]. Consider a random variable λ and denote it by $\lambda(s), s = 1, \dots, N_{\Omega}$, where s is the scenario index. N_{Ω} and Ω are the total number and set of scenarios. Accordingly, the set of possible realizations λ_{Ω} for a random variable λ is equal to $\lambda_{\Omega} = \{\lambda(1), \dots, \lambda(N_{\Omega})\}$.

The only difference between a random variable and a stochastic process is that the random values of a stochastic process evolve and have progress over time [119]. For example, the price of DA electricity market over 24 hours of a day is a stochastic process. In other words, a stochastic process can be created by random variables that are dependent and consecutively appear in time. For example, the price of DA electricity market at 1 pm is influenced by the prices in other 23 hours, and in **Error! Reference source not found.**, if λ i ndicates the 24 hours prices for the following day, $\lambda(s)$ should be a vector of 24×1 demonstrating one possible realization of DA electricity market prices.

2.5.2 Scenarios

It is mentioned in Section 2.5.1 that each scenario is a particular realization of a stochastic process, and using scenarios from a computational perspective is an appropriate way to distinguish stochastic processes.

To simply define a stochastic process and intending to cover its most credible realizations, it is essential to produce an adequate amount of scenarios initially. In order to do so, it is commonly needed to produce a vast number of scenarios, which in fact would be computationally difficult to deal with the related stochastic programming problem. Therefore, it is necessary to introduce a method to reduce the number of scenarios which is generated in the beginning. This specific method must keep the most important data in the stochastic process with remarkably less number of scenarios and the reduced scenarios must be representative enough.

2.5.3 Stochastic Programming Problems

In most stochastic decision-making problems, including electricity market decision-making problems, the optimal decisions by the operator have to be made with the lack of data during a decision horizon in which few stages are considered. The uncertainty in stochastic decision-making problems is partly or eliminated in each stage. In other words, the quantity of accessible data is not generally the same from stage to stage for the operator. Stochastic programming problems with a different number of stages (two-stage and multistage) are briefly explained in the following:

In the first type of stochastic programming decision-making problems, a two-stage problem is considered where the stochastic process is characterized using a set of scenarios formed in two stages.

In a two-stage decision-making problem, the decisions are separated and characterized into two stages: The first-stage decision which is called here-and-now decision is usually made before the stochastic process realization. The Second-stage decisions, which are called wait-and-see decisions, are made after the stochastic process realization. In other words, in the case of wait-and-see decisions, the decision-maker is supposed to be capable of waiting for realization of the random coefficients, while in the case of here-and-now decisions, the decision-maker is supposed to make decisions before and with no understanding of the realizations.

Fig. 2.14 shows the scenario tree for a two-stage problem. As can be seen from Fig. 2.14, a scenario tree includes several nodes in addition to the between branches. These nodes indicate the problem state points where required decisions are made. Each of these nodes is composed of a particular predecessor as well as numerous successors. As seen in the figure, the root is the first node related to the beginning of the decision framework where the first-stage decisions are completed. The nodes associated with the first node (root) are so-called the second-stage nodes and indicate the problem state points where the second-stage decisions are finalized. The number of scenarios is equal to the number of nodes in the second stage for a two-stage problem. In a problem with a two-stage scenario tree structure, a second-stage node is called leaf, and each branch indicates a realization of random variables.

It is noteworthy to mention that this two-stage problem is optimally solved as a single optimization problem. Two types of formulation are usually used to formulate a stochastic programming problem which is called node-variable and scenario-variable formulations. The node-variable formulation depends on variables related to decision points, while the scenario-variable formulation depends on variables related to scenarios. The size of the node-variable formulation is relatively smaller than the scenario-variable one and is mainly compatible with a straightforward solution, while the scenario-variable formulation needs much more variables and constraints. However, the scenario-variable formulation has a useable structure that is compatible with decomposition.

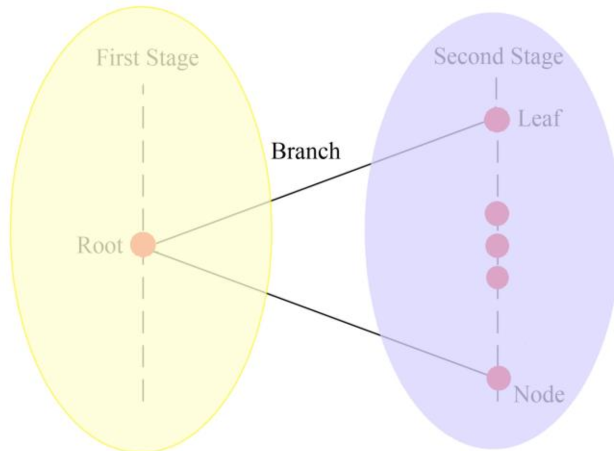


Fig. 2.14 A problem with a two-stage scenario tree structure.

In a real-life situation, generally most of the decision-making stochastic programming problems are in excess of two stages, and for these decision-making problems, two-stage problems are not valid and should be extended to a multi-stage decision-making problem.

Fig. 2.15 shows the scenario tree for a three-stage problem, which is a three-stage sample of a multi-stage problem. It can be clearly seen from Fig. 2.15 that a scenario tree comprises several nodes along with the branches in between. These nodes which are shown by red color point out the problem state points where decisions are made. As it is seen in the figure, the first node, which is called the root, indicates the beginning of the decision framework where the first-stage decisions are formed. The nodes linked to the first-stage decision node (root) are the second-stage nodes and indicate the problem state points where the second-stage is created. The amount of scenarios is equal to the number of the nodes in the last stage (e.g. third stage in a three-stage problem, as shown in Fig. 2.15) for a multi-stage problem. Also, in a multi-stage scenario tree, the nodes in the last stage are called a leave, and each branch designates a realization of random variables. Note that in multi-stage decision-making problems, the problem is also optimally solved as a single optimization problem.

2.5.4 Solving Stochastic Programming Problems

Due to the addition of scenarios to the stochastic programming problems, the amount of variables is usually amplified, making them large-scale problems with at least millions of variables. Therefore, it is significantly vital to wisely choose the number of scenarios to characterize the stochastic programming problem processes appropriately. On the other hand, scenario reduction techniques can be used to reduce the number of scenarios properly.

Also, stochastic programming problems usually comprise of nonlinear constraints that can be easily decomposed as linear ones by scenario approaches. Generally, decomposition methods are most suitable for dealing with these problems. More detail about decomposition methods are available in [126]. Also, Decomposition methods for linear stochastic programming problems can be found in [122].

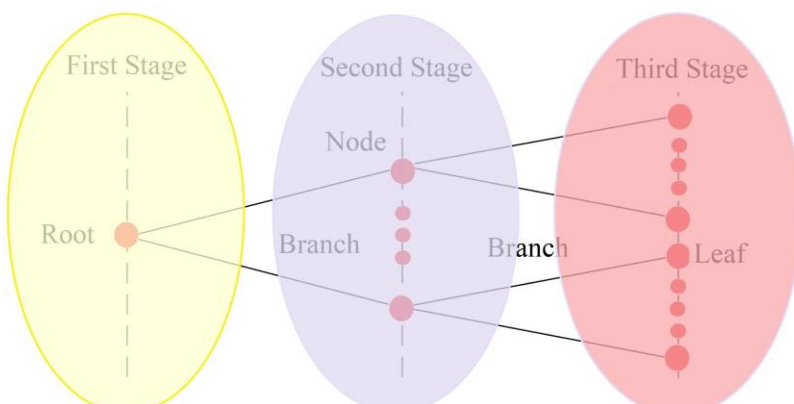


Fig. 2.15 A problem with a three-stage scenario tree structure.

2.6 Summary

This chapter has gone through the background, previous studies, and the conceptions of HPP and its operating systems and diverse kinds of HPP. Additionally, it has summarized the concepts of organization and agents involving in electricity markets such as producers, consumers, and retailers. The basics of stochastic programming have also been briefly provided.

3 Risk-Constrained Bidding Strategy for a Joint Operation of Wind Power and Compressed Air Energy Storage Aggregators

This chapter proposes a coordinated strategy of a hybrid power plant (HPP) which includes a wind power aggregator (WPA) and a commercial compressed air energy storage (CAES) aggregator to participate in three electricity markets (DA, intraday and balancing markets). The CAES aggregator has an extra ability which is called a simple-cycle mode operation which makes it work like a gas turbine when needed; this helps the HPP to economically handle the errors in the wind power and electricity price predictions. The coordinated strategy of the HPP is formulated as a three-stage stochastic optimization problem. To control the financial risks, the CVaR model is added to the optimization problem. Moreover, the proposed offering method is capable of submitting both bidding quantity and curves to the DA market. A mixed-integer linear programming formulation is obtained for the problem which can be easily solved by commercially available software such as GAMS. The models are tested on a realistic case study located in Spain, and the results show the applicability of the suggested method to increase the joint operation profit and reduce the financial risks.

3.1 Motivation

Recently, numerous studies have focused on self-scheduling approaches for CAES facilities and aggregators and analyzed the energy trading in different types of electricity markets to maximize their profit [91]. For instance, a co-optimized CAES model to clarify the importance of providing operating reserves and energy arbitrage in diverse electricity markets located in the United States is presented in [78]. Ref. [90] offers a risk-constrained bidding strategy for a commercial CAES aggregator that participates in a DA market. The CAES used in this study has an additional facility called simple-cycle mode, which works as an extra gas turbine.

On the other hand, many studies concentrate on the best offering strategies for WPAs to contribute to different types of electricity markets [67]. For example, in [70], a method is suggested to advance an offering strategy for a WPA participating in different electricity markets considering the uncertainties of the wind power and electricity market prices. Ref. [71] offers a strategy for a WPA to participate in a DA market by considering the WPA as a price-maker producer. Ref. [72] also offers a strategy for a WPA as a price-taker producer in a DA market, but as a price-maker producer in the real-time (balancing) market. Ref. [88] presents a new model considering the uncertainties of the wind power and loads for corrective voltage control to handle the condition when power systems have voltage instability because of unexpected failure and contingencies.

Besides, a variety of studies provide strategies for WPAs in conjunction with other types of aggregators [82, 92, 127]. For example, Ref. [77] analyses the combined operation of a pumped-storage unit and a WPA. The uncertainties included in this study are the wind power and market price fluctuations. In this regard, a very similar study is done in [78], which evaluates the impact of wind power uncertainties in a joint operation with a pumped-hydro aggregator. Ref. [79] offers a bidding strategy for a hydro aggregator and a WPA to contribute to a DA market. In this study, in order to control the financial risk, the CVaR is added to the model. Ref. [80] assesses two separate models comprising a joint operation of a WPA and a gas turbine aggregator, as well as a WPA and a CAES aggregator. An offering strategy for a WPA along with a flexible load (demand response provider) is provided in [85], which helps the WPA to handle the wind uncertainties. To minimize the operational cost and imbalance payments due to the wind power imbalances, an offering strategy for controlling critical peak pricing events is assessed in [86]. The strategy is done from the viewpoint of a demand response aggregator which owns a wind facility. Ref. [87] provides a bidding strategy for a WPA and a demand response provider to contribute to the intraday market along with DA and balancing markets.

3.2 Contributions

This chapter proposes a framework in which a WPA can compensate its deviation between the actual and forecasted value of wind generation by the coordinated operation with a commercial CAES aggregator in the form of an HPP. HPP gathers information from the WPA and CAES and takes part in DA, intraday, and balancing markets. The uncertainties of the WPA production and the three mentioned market prices are considered stochastic using the stochastic programming method. To find the best bidding strategy, which also controls the financial risk, the CVaR is added to the stochastic programming model.

The contributions of the chapter are given as follows:

- The development of a two-stage stochastic decision-making model for the participation of CAES aggregator equipped with a simple-cycle mode operation which gives it the ability to work as a gas turbine in both DA and intraday markets.

- The development of an optimal offering strategy model for the joint operation of a WPA and a CAES aggregator as an HPP to maximize their expected profit and also to mitigate wind power uncertainties.
- The implementation and analysis of the proposed framework on three different electricity markets in a realistic case study.
- A robust risk constrained HPP model to overcome the financial risks of electricity markets.

3.3 WPA Modeling

3.3.1 Introduction to WPA

The number of wind farms and producers with significant utilization of wind power resources is exponentially growing all over the world. At this moment, being a wind power producer is a worthwhile and money-making investment. The major reason for wind power developments is the increase and fluctuation of fossil fuel prices, especially the oil price. For example, from 1985 to September 2003, the price of a barrel of crude oil on NYMEX was normally less than US$25/barrel. For the year 2003, the price of crude oil was increased up to US$30/barrel, and then from the beginning of 2004 to August 2005 gradually increased to US$60/barrel, and even experienced an unbelievable price of US$147.30/barrel in July 2008.

However, three straightforward features distinguish the conventional non-renewable producers from wind power producers from the energy-selling viewpoint. The first feature is the WPA's emission-free productions, which is usually supported by governments. The second feature is their almost zero cost and no fuel consumption. The third feature is a negative feature though, i.e., wind power generation is uncertain and usually cannot be precisely predicted. The third feature leads to a non-dispatchable output and makes the wind energy trading quite risky.

Even though the first and second features undoubtedly improve the involvement of WPAs in electricity markets, the third feature, the uncertainty of wind power production, creates the main problem to the regular involvement of WPAs in electricity markets. This problem includes both technical and economic ones, which makes it difficult for a WPA to stay alive in competitive electricity markets exclusively intended for conventional deterministic producers.

From a technical point of view, the right running of WPA uncertainty is mostly accomplished using a balancing market that lets WPAs compensate for their lack of production or even selling their excess production.

From an economic view, the market operator determines the balancing market prices that are usually less profitable for producers than other markets such as DA and intraday markets. Consequently, as WPA's survival depends on the balancing market to balance its energy production, its cost-effectiveness declines in comparison with other types of producers especially those who have deterministic resources and can participate in electricity markets such as DA and intraday markets.

So far, three main approaches have been developed by regulators in order to overcome this issue. In the first approach, WPAs are directly controlled by the market operator as a negative demand, and WPAs are paid with a fixed price for their real-time energy production. This approach allows the WPAs to decrease the financial risk. However, WPAs lose the chance of making a higher profit through participating in all markets when the price of electricity peaks. In the second approach, WPAs participate only in balancing market, in which they make a profit by selling their real-time energy production like other producers as well as receiving a subsidy from the government to support them. Finally, in the third approach, which is used in this thesis, WPAs must participate in electricity markets like any other producers without receiving any subsidies from the government.

For competing with other producers in a severely competitive environment, one of the most effective ways for a WPA is to use or coordinated with other producers such as conventional power plants, energy storages, and demand response programs. However, other producers, such as conventional power plants, have no strong motivation to work with WPAs [77, 128-130]. Another effective way for a WPA to compete with other producers in a competitive environment is to exploit less uncertain markets such as future markets and options [131].

3.3.2 Decision Framework

In this chapter, it is assumed that a WPA participates in three pool-based electricity markets, including DA, intraday, and balancing markets. It is also assumed that the WPA has no market-power capability in any of the markets mentioned above. The objective function considered in these problems is to maximize the expected profits of the WPA in all mentioned pool-based electricity markets.

Fig. 3.1 shows the time framework for the three electricity markets. As can be seen from Fig. 3.1, for the next operating day D+1, the DA market is cleared in day D, and the intraday market is cleared after the DA market and a couple of hours before the day D+1. Due to later clearance of the intraday market in comparison with the DA market, the intraday market has fewer uncertainties and is an excellent opportunity for the WPA to compensate for its deficient production. For the sake of simplicity, it is assumed that the intraday market is cleared two and a half hours before the day D+1, as shown in Fig. 3.1. Also, the balancing market guarantees the balance between power production and consumption by compensating the differences between the actual power and the scheduled one. Accordingly, the balancing market is cleared close to each energy delivery period (10 to 15 minutes) of day D+1. Consequently, using this latter market, energy imbalance between generation and consumption is balanced and evaluated.

In summary, a WPA competing in the market structure mentioned above has to firstly decide to optimally participate in the DA market, secondly modify its forecasted energy and participate in the intraday market, and finally adjust its produced energy deviations and participate in the balancing market.

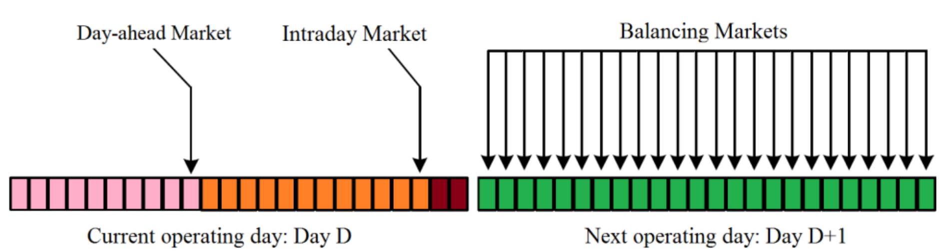


Fig. 3.1 Three electricity markets framework

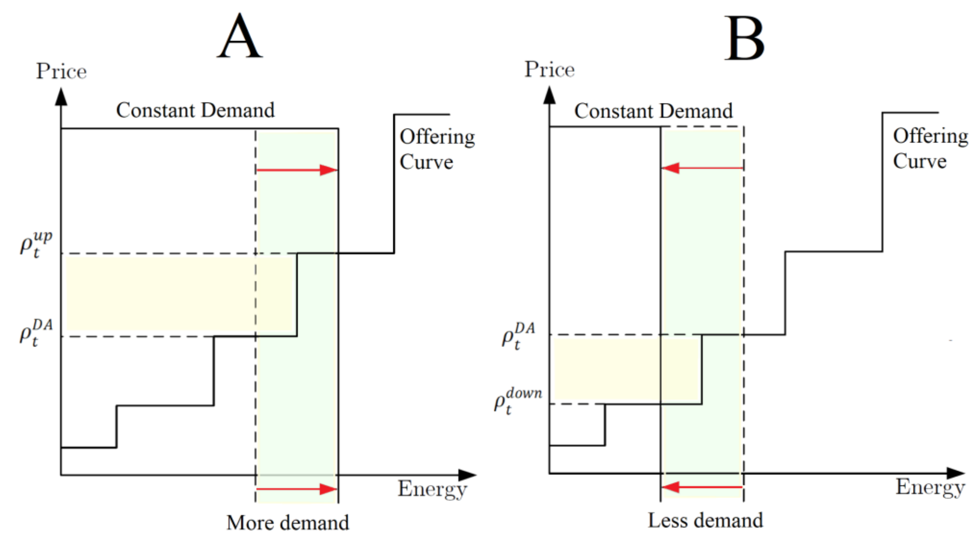


Fig. 3.2 Imbalance price clearance for more demand or less demand

3.3.3 Mechanism for Imbalance Prices

In this chapter, the balancing market is used to assure the balance between energy production provided by WPAs and its scheduled energy offered to other pool-based electricity markets such as DA and intraday markets. As mentioned earlier in this chapter, balancing markets are usually cleared very near to the actual energy supply time when there are much fewer uncertainties in the market and WPAs have very precise knowledge about their wind power production levels. Therefore, it is confidently assumed that every WPA participates in the balancing market with no uncertainties.

Every WPA tends to adjust its energy deviations using balancing markets if the final wind power production is less or more than the power scheduled in the previous pool-based electricity markets such as DA and intraday markets. These energy deviations can be either positive, when there is a higher wind power production or negative when there is a lower wind power production in each hour of day D+1 (see Fig. 3.1). Accordingly, every WPA with energy deviations must sell its extra produced power to or buy for its deficient power production from the balancing market, respectively. It is worthwhile to mention that the final price of selling and buying in the balancing market is determined by the market operator after receiving and analyzing the offering or bidding powers from producers and consumers.

Fig. 3.2 shows the imbalance price clearance for negative and positive system imbalance. As can be seen from Fig. 3.2, it is assumed that the price of the DA market ρ_t^{DA} is achieved as the connecting point of the offering and demand curves (the planned demand curve with a dashed vertical line in both Fig. 3.2(A) and (B)). Note that, for the sake of simplicity, the activities of consumers are assumed to be entirely constant. The offering curve is similarly created from the all energy producers offers.

However, the price ρ_t^+ for positive energy deviations (*i.e.* producing higher productions than planned) and the price ρ_t^- for negative energy deviations (*i.e.* producing lower productions than planned) are established for each period in the balancing market. These introduced positive and negative prices ρ_t^+ and ρ_t^- indicate the required energy cost to offset the system imbalance as defined as follows:

- If there is a lack of energy production or more demand as shown in Fig. 3.2(A) (the actual demand curve with solid vertical line), then Eqs. (3.1) and (3.2) can be defined:

$$\rho_t^+ = \rho_t^{DA} \tag{3.1}$$

$$\rho_t^- = \max(\rho_t^{DA}, \rho_t^{up}) \tag{3.2}$$

where ρ_t^{up} is defined as the price to which the energy price is required to be increased, as explicitly shown in Fig. 3.2(A). In this condition, the market decision-maker arranges a balancing market in which the producers, including WPAs, can participate and buy for their deficient production. It is essential to mention that as the energy price ρ_t^{up} is usually more than the DA market price ρ_t^{DA}, the producers who participate in the balancing market need to pay more cost in comparison with the DA market.

- If there are extra energy productions or less demand, as shown in Fig. 3.2(B) (the actual demand curve with solid vertical line), Eqs. (3.3) and (3.4) can be defined:

$$\rho_t^{+} = \min(\rho_t^{DA}, \rho_t^{down}) \tag{3.3}$$

$$\rho_t^{-} = \rho_t^{DA} \tag{3.4}$$

where ρ_t^{down} is the price to which the energy price is required to be reduced, as clearly shown in Fig. 3.2(B). In this circumstance, the market operator organizes a balancing market in which all producers, including WPAs, can contribute and sell their excess production. Note that as the energy price ρ_t^{down} is usually less than DA market ρ_t^{DA}, the producers who contribute to the balancing market achieve less profit in comparison with the DA market.

3.3.4 WPA Profit and Imbalance Cost

Imagine a WPA is scheduled to provide the energy level Ew_t^{DA} to the DA market for period t, but actually produces Ew_t. If the price of the DA market is cleared by the market operator which is equal to ρ_t^{DA}, and the profit from the balancing market is equal to B_t, then the profit Zw_t of this WPA can be formulated as (3.5). Note that, in this section, no intraday market is considered for simplicity.

$$Zw_t = \rho_t^{DA} Ew_t^{DA} + B_t, \tag{3.5}$$

It is essential to mention that the balancing market profit B_t can sometimes be negative, which means there is a cost resulting from balancing market process for the WPA. In general, the total deviation Δw_t experienced by the WPA is equal to the actual energy produced by WPA Ew_t minus the WPA scheduled energy Ew_t^{DA} which can be positive or negative as formulated in (3.6):

$$\varepsilon w_t = Ew_t - Ew_t^{DA}, \tag{3.6}$$

Accordingly, the profit or cost from the balancing market B_t for a WPA can be defined as follows:

$$B_t = \begin{cases} \rho_t^+ \varepsilon w_t, & \varepsilon w_t \geq 0 \\ \rho_t^- \varepsilon w_t, & \varepsilon w_t < 0. \end{cases} \tag{3.7}$$

As stated by (3.7), a positive or negative deviation means excessive or deficient production from WPA, respectively. Accordingly, the WPA will be paid by the price ρ_t^+ for its excess of energy production and will be charged by the price ρ_t^- for its deficient production. In order to use the price of the DA market for (3.7), the following can be defined:

$$\eta_t^+ = \frac{\rho_t^+}{\rho_t^{DA}}, \quad \eta_t^+ \leq 1, \tag{3.8}$$

$$\eta_t^- = \frac{\rho_t^-}{\rho_t^{DA}}, \quad \eta_t^- \geq 1 \tag{3.9}$$

From these two definitions, Eq. (3.7) can be rewritten as (3.10):

$$B_t = \begin{cases} \eta_t^+ \rho_t^{DA} \varepsilon w_t, & \varepsilon w_t \geq 0 \\ \eta_t^- \rho_t^{DA} \varepsilon w_t, & \varepsilon w_t < 0. \end{cases} \quad (3.10)$$

Now after defining the profit or cost B_t from the balancing market, Eq. (3.5) can be reformulated as two separate cases:

1) If there are extra wind energy productions and the energy deviation εw_t experienced by the WPA is positive ($\varepsilon w_t \geq 0$), then by substituting (3.10), $B_t = \eta_t^+ \rho_t^{DA} \varepsilon w_t$, into (3.5), the profit Zw_t can be redefined as (3.11):

$$Zw_t = \rho_t^{DA} Ew_t^{DA} + \eta_t^+ \rho_t^{DA} \varepsilon w_t, \quad \varepsilon w_t \geq 0. \quad (3.11)$$

By substituting Ew_t^{DA} from (3.6), i.e., $Ew_t - \varepsilon w_t$, into (3.11), Eq. (3.11) can be altered as follows:

$$Zw_t = \rho_t^{DA}(Ew_t - \varepsilon w_t) + \eta_t^+ \rho_t^{DA} \varepsilon w_t = \rho_t^{DA} Ew_t - \rho_t^{DA}(1 - \eta_t^+)\varepsilon w_t, \quad \varepsilon w_t \geq 0, \quad (3.12)$$

2) If there is a lack of wind energy production and the energy deviation εw_t experienced by the WPA is negative ($\varepsilon w_t < 0$), then by substituting (3.10), $B_t = \eta_t^- \rho_t^{DA} \varepsilon w_t$, into (3.5), the profit Zw_t in this situation can be defined as (3.13):

$$Zw_t = \rho_t^{DA} Ew_t^{DA} + \eta_t^- \rho_t^{DA} \varepsilon w_t, \quad \varepsilon w_t < 0\,. \quad (3.13)$$

Similar to the previous case, by substituting Ew_t^{DA} from (3.6) into (3.13), Eq. (3.13) can be rewritten as follows:

$$Zw_t = \rho_t^{DA}(Ew_t - \varepsilon w_t) + \eta_t^- \rho_t^{DA} \varepsilon w_t = \rho_t^{DA} Ew_t - \rho_t^{DA}(1 - \eta_t^-)\varepsilon w_t, \quad \varepsilon w_t < 0, \quad (3.14)$$

If the common form is used, Eqs. (3.13) and (3.14) can be written as follows:

$$Zw_t = \rho_t^{DA} Ew_t - Qw_t, \quad (3.15)$$

where

$$Qw_t = \begin{cases} \rho_t^{DA}(1 - \eta_t^+)\varepsilon w_t, & \varepsilon w_t \geq 0 \\ \rho_t^{DA}(\eta_t^- - 1)\varepsilon w_t, & \varepsilon w_t < 0. \end{cases} \quad (3.16)$$

The first term $\rho_t^{DA} Ew_t$ in (3.16) sets up the maximum amount of profit that the WPA may accumulate from selling its produced energy production when the WPA has a thorough data about its upcoming wind energy production, and there is no uncertainty for its energy output. The last term Qw_t corresponds to the above-mentioned profit or cost which is a consequence of selling the positive energy deviations ($\varepsilon w_t \geq 0$) or buying the negative energy deviations ($\varepsilon w_t < 0$) in the balancing market. The profit or cost mentioned above is generally called imbalance cost and can also be inferred as the cost related to inadequate predictions of wind energy production. In a usually very rare situation in which the WPA perfectly predicts its future wind generation, and there are no positive or negative energy deviations ($\varepsilon w_t = 0$) in the balancing market for the WPA, there is no imbalance cost and Qw_t will be zero in (3.50). Furthermore, it is important to mention that, as $\rho_t^{DA} Ew_t$ in (3.16) is the term that cannot be controlled, in order to maximize (3.16), the imbalance cost Qw_t should be minimized.

However, if the intraday market is added to the analysis mentioned above, the characterization of imbalance cost turns out to be slightly vague as a result of the price changes between the DA and intraday markets. Apart from this vagueness and complexity, it is very obvious that, even if there is an intraday market, all market agents who have uncertainties in their energy production including WPAs are obliged to finally amend their positive or negative energy deviations in the balancing market.

3.3.5 Certainty Gain Effect

The intraday market is a market similar to DA market intended to let all market agents who have uncertainties in their energy production including WPAs to adjust their energy production schedule according to the formerly gained market price results and their modified energy production predictions. Therefore, the intraday market is planned after the DA market and may cover the duration similar to the DA market. In addition to this service, the intraday market offers the other market agents who do not have uncertainties in their energy production, such as conventional power plants with an extra chance of participating in pool-based markets and make additional profit by manipulation of the energy price changes between these two markets.

Thanks to the later clearance of intraday market in comparison with the DA market, it is notably more beneficial for WPAs since the level of uncertainty is lower and the WPAs can have a better forecast for its energy production. For instance, the predictions of wind three hours in advance are considerably more precise than the predictions one day before. This certainty improvement is a phenomenon that is called certainty gain effect which is a financial surplus that the WPA gains if it offers to the DA market while it knows there is an intraday market to be offered with fewer uncertainties in its forthcoming wind energy production.

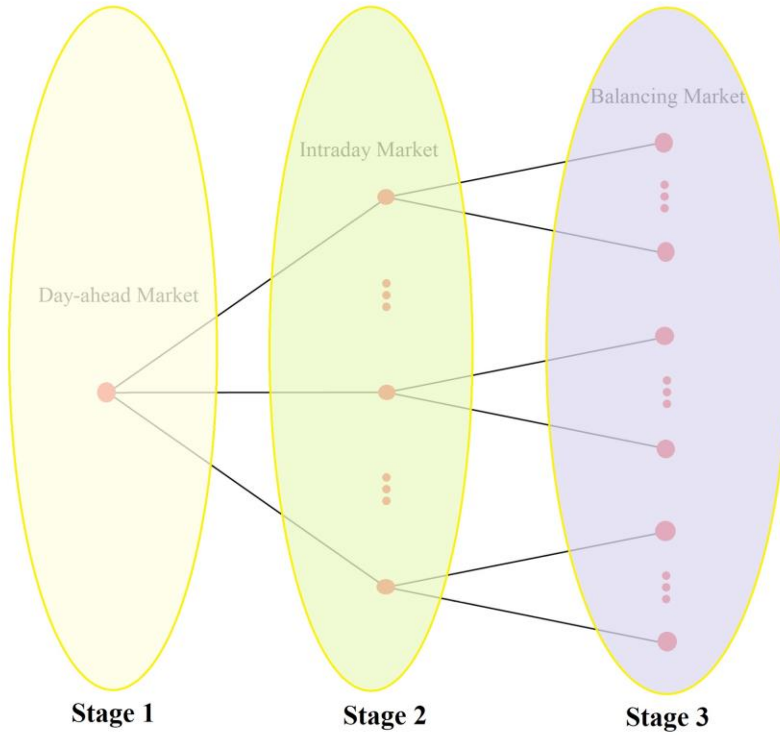


Fig. 3.3 Scenario tree to describe the uncertainties of pool-based market prices and wind generation in a WPA problem

3.3.6 Scenario Tree

A scenario tree describing the uncertainties related to market prices in addition to wind generation in a WPA problem participating in three electricity markets, including DA, intraday, and balancing markets can be described, as shown in Fig. 3.3. In order to build this scenario tree, firstly, DA market price and wind power scenarios are produced, and then for each realization of these generated scenarios, some scenarios are generated to model the changes between DA and intraday market prices and the wind powers. In the next step, for each of these generated scenarios for the two market prices, imbalance price ratio scenarios are generated to model the balancing market.

3.3.7 WPA Basic Model

For the sake of simplicity, in the first step of modeling the WPA optimization problem, the intraday market is not considered. By considering the DA market and the imbalance cost of the balancing market, the optimization problem intended to maximize the expected profit of a WPA can be formulated as (3.17):

$$\text{Max}_{Pw_t^{DA},\forall t;\varepsilon w_{t,s},\forall t,s}\left[\mathcal{Z}_{Profit}^{WPA}\right]$$

$$\left[\mathcal{Z}_{Profit}^{WPA}\right]=\sum_{s=1}^{N_S}\sum_{t=1}^{N_T}\pi_s\left[\rho_{t,s}^{DA}.Pw_t^{DA}d_t+B_{t,s}\right]. \tag{3.17}$$

where N_s and N_T are the total number of scenarios and periods of time, respectively. π_s is the probability of occurrence of scenario *s*, and d_t is the time interval. This optimization problem maximizes the expected profit gained by the WPA from trading its wind power production in the two markets mentioned above. The objective function (3.17) is subject to constraints (3.18) and (3.19):

$$0\leq Pw_t^{DA}\leq Pw^{Max},\quad \forall t \tag{3.18}$$

$$\varepsilon w_{t,s}=Ew_{t,s}-Ew_t^{DA}=d_t(Pw_{t,s}-Pw_t^{DA}),\quad \forall t,s \tag{3.19}$$

where constraint (3.18) limits the offering power of WPA to the DA market, and Pw^{Max} is the maximum capacity of WPA. Eq. (3.19) formulates the total deviation $\varepsilon w_{t,s}$ experienced by the WPA for each period of time t and scenario s which can be positive or negative based on the excess or deficiency of energy produced by WPA. The profit or cost $B_{t,s}$ from the balancing market for each period of time t and scenario s can be defined as in (3.20):

$$B_{t,s}=\begin{cases}\eta_{t,s}^{+}\rho_{t,s}^{DA}\varepsilon w_{t,s}, & \varepsilon w_{t,s}\geq 0\\ \eta_{t,s}^{-}\rho_{t,s}^{DA}\varepsilon w_{t,s}, & \varepsilon w_{t,s}<0\end{cases}\quad \forall t,s \tag{3.20}$$

As the profit or cost from the balancing market $B_{t,s}$ in the WPA optimization problem (3.17)-(3.20) is a piecewise function and does not let the problem be solved by optimization methods, a binary variable $\Gamma_{t,s}$ demonstrating whether the total deviation is positive or negative can be simply defined and added to the problem formulation to avoid this difficulty. Therefore, the WPA optimization problem (3.17)-(3.20) can be rewritten as the one in (3.21)-(3.26):

$$\mathrm{Max}_{Pw_t^{DA},\forall t;\varepsilon w_{t,s},\forall t,s}\left[\mathcal{Z}_{Profit}^{WPA}\right]$$

$$\left[\mathcal{Z}_{Profit}^{WPA}\right]=\sum_{s=1}^{N_S}\sum_{t=1}^{N_T}\pi_s\left[\rho_{t,s}^{DA}.Pw_t^{DA}d_t+\eta_{t,s}^{+}\rho_{t,s}^{DA}\varepsilon w_{t,s}\left(1-\Gamma_{t,s}\right)+\eta_{t,s}^{-}\rho_{t,s}^{DA}\varepsilon w_{t,s}\Gamma_{t,s}\right] \tag{3.21}$$

subject to

$$0\leq Pw_t^{DA}\leq Pw^{Max},\quad \forall t \tag{3.22}$$

$$\varepsilon w_{t,s}=Ew_{t,s}-Ew_t^{DA}=d_t(Pw_{t,s}-Pw_t^{DA}),\quad \forall t,s \tag{3.23}$$

$$\varepsilon w_{t,s}\leq \varkappa(1-\Gamma_{t,s}),\quad \forall t,s \tag{3.24}$$

$$-\varepsilon w_{t,s}\leq \varkappa\Gamma_{t,s},\quad \forall t,s \tag{3.25}$$

$$\Gamma_{t,s}=(0,1),\quad \forall t,s \tag{3.26}$$

where $\varkappa$ is a large number which is higher than any possible amount of $\left|\varepsilon w_{t,s}\right|$. It is important to mention that the value of the binary variable $\Gamma_{t,s}$ is equal to 1 if the energy deviation $\varepsilon w_{t,s}$ experienced by the WPA in time t and scenario s is negative (lack of wind power production), and is equal to 0 if the energy deviation $\varepsilon w_{t,s}$ experienced by the WPA in time t and scenario s is positive (excess of wind power production).

The WPA optimization problem (3.21)-(3.26) is a mixed-integer non-linear programming problem. It is an integer problem due to the usage of $\Gamma_{t,s}$ binary variable. Also, it is non-linear as a result of the product of variables ($\varepsilon w_{t,s}(1-\Gamma_{t,s})$ and $\varepsilon w_{t,s}\Gamma_{t,s}$) in (3.21). Solving a mixed-integer non-linear programming problem is generally difficult due to the absence of mathematical methods to find certified solutions. However, the WPA optimization problem (3.21)-(3.26) can be simply converted into a mixed-integer linear programming problem. To do so, the energy deviation $\varepsilon w_{t,s}$ is decomposed into two separate energy deviations presenting positive and negative energy deviations. After this decomposing $\varepsilon w_{t,s}$ into sum a of the $\varepsilon w_{t,s}^{+}$ and $\varepsilon w_{t,s}^{-}$, the problem formulation (3.21)-(3.26) is transformed into problem (3.27)-(3.33):

$$\mathrm{Max}_{Pw_t^{DA},\forall t;\varepsilon w_{t,s}^{+},\forall t,s;\varepsilon w_{t,s}^{-},\forall t,s}\left[\mathcal{Z}_{Profit}^{WPA}\right]$$

$$\left[\mathcal{Z}_{Profit}^{WPA}\right]=\sum_{s=1}^{N_S}\sum_{t=1}^{N_T}\pi_s\left[\rho_{t,s}^{DA}.Pw_t^{DA}d_t+\eta_{t,s}^{+}\rho_{t,s}^{DA}\varepsilon w_{t,s}^{+}-\eta_{t,s}^{-}\rho_{t,s}^{DA}\varepsilon w_{t,s}^{-}\right] \tag{3.27}$$

subject to

$$0\le Pw_t^{DA}\le Pw^{Max},\quad \forall t \tag{3.28}$$

$$\varepsilon w_{t,s}=Ew_{t,s}-Ew_t^{DA}=d_t(Pw_{t,s}-Pw_t^{DA}),\quad \forall t,s \tag{3.29}$$

$$\varepsilon w_{t,s}=\varepsilon w_{t,s}^{+}-\varepsilon w_{t,s}^{-},\quad \forall t,s \tag{3.30}$$

$$0\le \varepsilon w_{t,s}^{+}\le \varkappa_1(1-\Gamma_{t,s}),\quad \forall t,s \tag{3.31}$$

$$0\le \varepsilon w_{t,s}^{-}\le \varkappa_2\Gamma_{t,s},\quad \forall t,s \tag{3.32}$$

$$\Gamma_{t,s}=(0,1),\quad \forall t,s \tag{3.33}$$

where $\varkappa_1$ and $\varkappa_2$ are large numbers which are higher than any possible amount of $\varepsilon w_{t,s}^{+}$ and $\varepsilon w_{t,s}^{-}$, respectively. Proper values can be chosen for $\varkappa_1$ and $\varkappa_2$ with two simple ideas. Firstly, the maximum of $\varepsilon w_{t,s}^{+}$ happens in scenarios where the WPA does not sell any energy to the DA market that is $Pw_t^{DA} = 0$, but it finally produces $Pw_{t,s}$ of power. For that reason, the constant $\varkappa_1$ can be fixed to $Pw_{t,s}$. In the same way, the maximum of $\varepsilon w_{t,s}^{-}$ occurs in scenarios where the WPA sells its maximum capacity in the DA market that is $Pw_t^{DA} = Pw^{Max}$, but its ultimate production $Pw_{t,s}$ is equal to 0. Therefore, the constant $\varkappa_2$ can be fixed to Pw^{Max}.

As for each pried of time t and scenario s, the total energy deviation $\varepsilon w_{t,s} = \varepsilon w_{t,s}^{+} - \varepsilon w_{t,s}^{-}$ in (3.30) experienced by the WPA in the optimization problem guarantees that one of the variables $\varepsilon w_{t,s}^{+}$ or $\varepsilon w_{t,s}^{-}$ is equal to 0 thanks to the fact that $\eta_{t,s}^{+} \leq 1$ and $\eta_{t,s}^{-} \geq 1$ in (3.8) and (3.9). Therefore, the binary variable $\Gamma_{t,s}$ is actually not needed, and consequently, the WPA optimization problem (3.27)-(3.33) which is a mixed-integer programming problem can be equally altered into a linear programming problem (3.34)-(3.39):

$$\text{Max}_{Pw_t^{DA},\forall t;\varepsilon w_{t,s}^{+},\forall t,s;\varepsilon w_{t,s}^{-},\forall t,s}\left[\mathcal{Z}_{Profit}^{WPA}\right]$$

$$\left[\mathcal{Z}_{Profit}^{WPA}\right] = \sum_{s=1}^{N_S}\sum_{t=1}^{N_T}\pi_s\left[\rho_{t,s}^{DA}.Pw_t^{DA}d_t + \eta_{t,s}^{+}\rho_{t,s}^{DA}\varepsilon w_{t,s}^{+} - \eta_{t,s}^{-}\rho_{t,s}^{DA}\varepsilon w_{t,s}^{-}\right] \tag{3.34}$$

subject to

$$0 \leq Pw_t^{DA} \leq Pw^{Max}, \quad \forall t \tag{3.35}$$

$$\varepsilon w_{t,s} = Ew_{t,s} - Ew_t^{DA} = d_t(Pw_{t,s} - Pw_t^{DA}), \quad \forall t,s \tag{3.36}$$

$$\varepsilon w_{t,s} = \varepsilon w_{t,s}^{+} - \varepsilon w_{t,s}^{-}, \quad \forall t,s \tag{3.37}$$

$$0 \leq \varepsilon w_{t,s}^{+} \leq Pw_t^{DA}d_t, \quad \forall t,s \tag{3.38}$$

$$0 \leq \varepsilon w_{t,s}^{-} \leq Pw^{Max}d_t, \quad \forall t,s \tag{3.39}$$

3.3.8 Offering Curves

The WPA optimization problem (3.34)-(3.39) is formulated to achieve the optimal single value instead of optimal offering curves for every hour of the DA. However, it is more appropriate to attain optimal offering curves for a WPA to be submitted to the DA market. To do so, variables Pw_t^{DA} must be extended to all scenarios as $Pw_{t,s}^{DA}$ and the constraints (3.40) and (3.41) must be added to the WPA optimization problem (3.34)-(3.39),

$$\left(Pw_{t,s}^{DA} - Pw_{t,s'}^{DA}\right).\left(\rho_{t,s}^{DA} - \rho_{t,s'}^{DA}\right) \geq 0 \quad \forall t, \forall s, \forall s' \tag{3.40}$$

$$Pw_{t,s}^{DA} = Pw_{t,s'}^{DA}, \quad \forall t, s, s': \quad \rho_{t,s}^{DA} = \rho_{t,s'}^{DA}. \tag{3.41}$$

Constraint (3.40) is intended to make offering curves to be non-decreasing, which is an obligation in mostly all electricity markets. Constraint (3.41) is also used for a non-anticipativity formulation as only one offering curve can be submitted to the DA market for each hour. It is important to mention that the new model with (3.41) has fewer constraints due to the removal of too many constraints by non-anticipativity formulation.

3.3.9 Risk Modeling

In a stochastic programming decision-making problem, the problem is usually formulated to maximize an objective function demonstrating an expected profit or minimize an objective function demonstrating cost. By default, these minimization or maximization problems are considered and modeled to be risk-neutral which means the operator only tries to maximize the expected value of the profit and minimize the cost while paying no attention to the characteristics of the distribution of the profit or cost.

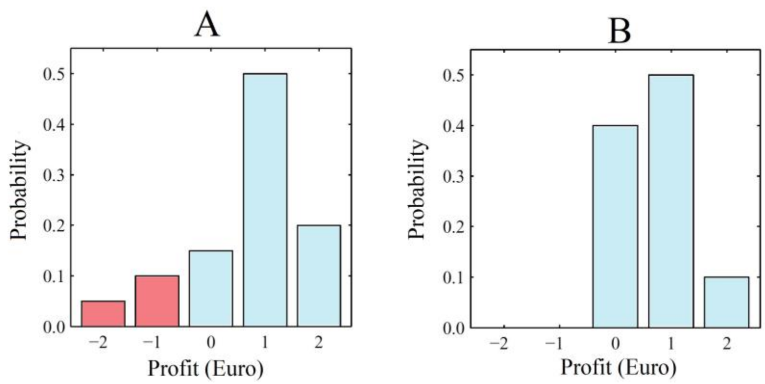


Fig. 3.4 Concept of risk

On the other hand, to maximize the expected value of the profit or minimize the cost, the operator can also evaluate the scenarios with worse profit values considering risk and solve a risk-averse problem.

Fig. 3.4 demonstrates the concept of risk. As can be seen from Fig. 3.4, there are two examples of profit variables probability mass functions that are signified by A and B. The expected profit of A and B are equal to 0.7 Euros. Consequently, both expected profits are similarly acceptable for an operator with a risk-neutral standpoint. However, the profit of B is positive at all times, and the operator does not lose any money in all scenarios. In contrast, the profit of A is negative in two scenarios, as shown by the red color in Fig. 3.4, and the operator loses money in two scenarios. Therefore, even with having the same expected profit, A is considered to be riskier than B.

Note that the operator can set different risk factors for a stochastic programming problem considering risk, which allows him/her to achieve different expected profits with different objective function variability.

For instance, a consumer may participate in the DA market by bidding strategies pursuing the minimum cost and ignoring cost variability. On the other hand, this consumer may pursue the minimum cost but restricting the variance of the cost distribution it attains. Strategies achieved by solving these different models would usually be quite different.

Since the amount of risk factor is an input parameter, operators should previously identify the amount of risk factor they want to choose.

The easiest way to regulate the risk of financial profit in the WPA optimization problem (3.34)-(3.41) is to add the CVaR at the σ confidence level to the optimization problem. Adding the CVaR to the WPA optimization problem does not change mathematical assets, and the problem still can be linear. The risk-constrained WPA optimization problem can be defined as follows [100],

$$\mathrm{Max}_{Pw_{t,s}^{DA},\forall t;\varepsilon w_{t,s}^{+},\forall t,s;\varepsilon w_{t,s}^{-},\forall t,s;\varphi_{s,\forall s};\theta}\left[\mathcal{Z}_{Profit}^{WPA}\right]+\zeta\left(\theta-\frac{1}{(1-\sigma)}\sum_{s=1}^{N_s}\pi_s\varphi_s\right) \tag{3.42}$$

subject to constraints (3.35)-(3.41) in addition to constraints (3.43) and (3.44),

$$-\sum_{t=1}^{N_T}\pi_s\left[\rho_{t,s}^{DA}.Pw_t^{DA}d_t+\eta_{t,s}^{+}\rho_{t,s}^{DA}\varepsilon w_{t,s}^{+}-\eta_{t,s}^{-}\rho_{t,s}^{DA}\varepsilon w_{t,s}^{-}\right]+\theta-\varphi_s\leq 0,\quad \forall s \tag{3.43}$$

$$\varphi_s\geq 0,\quad \forall s \tag{3.44}$$

where θ is a supplementary variable to calculate CVaR. φ_s is continuous non-negative variable to calculate CVaR. The risk-constrained WPA optimization objective function (3.42) comprises the expected profit ($\left[\mathcal{Z}_{Profit}^{WPA}\right]$ in (3.14)) and the CVaR multiplied by the risk factor ζ with the values between 0 for not considering the financial risk and 1 for fully considering the financial risk. Noteworthily, as shown in Fig. 3.5, $(1-\sigma)$ regulates the area of the profit distribution function covering the least profitable scenarios. More information about CVaR modeling is provided in [100, 132].

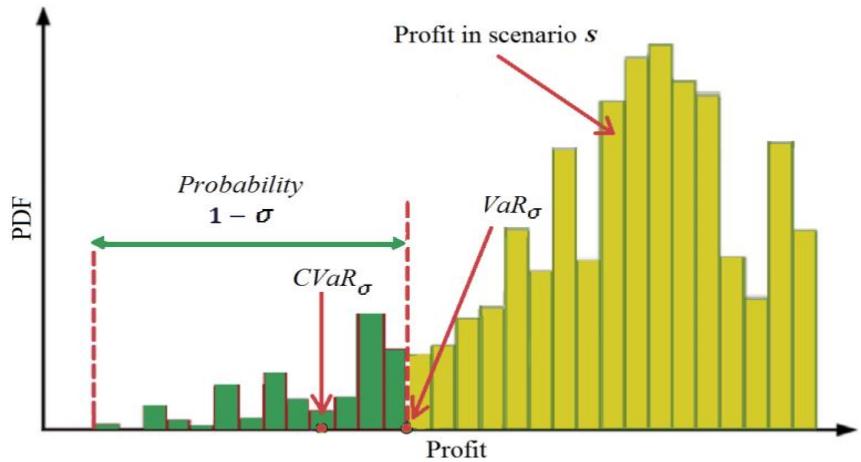


Fig. 3.5 CVaR to control the financial risks

3.3.10 Intraday Market

Three changes will be made if the intraday market is added to the WPA basic model in Subsection 3.3.7. Firstly, a term for the benefit/cost is added to the objective function of the WPA basic model that shows how much the WPA gains/loses from selling/buying energy in the intraday market. This added term can be clearly seen in the following:

$$[\mathcal{Z}_{Profit}^{WPA}] = \sum_{s=1}^{N_S}\sum_{t=1}^{N_T}\pi_s\left[\rho_{t,s}^{DA}.Pw_t^{DA}d_t + \rho_{t,s}^{IN}.Pw_t^{IN}d_t + \eta_{t,s}^{+}\rho_{t,s}^{DA}\varepsilon w_{t,s}^{+} - \eta_{t,s}^{-}\rho_{t,s}^{DA}\varepsilon w_{t,s}^{-}\right] \tag{3.45}$$

where $\rho_{t,s}^{IN}.Pw_t^{IN}d_t$ is the benefit/cost that the WPA gets/loses from/to the intraday market. Note that term $\rho_{t,s}^{IN}.Pw_t^{IN}d_t$ in (3.45) can be sometimes negative if the WPA chooses to buy energy from the intraday market ($Pw_t^{IN} < 0$). Secondly, the total energy deviation $\varepsilon w_{t,s}$ is calculated based on the final energy schedule $Ew_{t,s}^{SC}$. The final power schedule $Pw_{t,s}^{SC}$ which can be easily converted to the final energy schedule $Ew_{t,s}^{SC}$ is calculated based on (3.46).

$$Pw_{t,s}^{SC} = Pw_{t,s}^{DA} + Pw_{t,s}^{IN}, \quad \forall t, \forall s \tag{3.46}$$

$$0 \leq Pw_{t,s}^{SC} \leq Pw^{Max}, \quad \forall t, s \tag{3.47}$$

$$\varepsilon w_{t,s} = Ew_{t,s} - Ew_{t,s}^{SC} = d_t(Pw_{t,s} - Pw_{t,s}^{SC}), \quad \forall t, s \tag{3.48}$$

Finally, constraints related to non-anticipativity of intraday market can be added to the WPA basic model as follows:

$$Pw_{t,s}^{IN} = Pw_{t,s'}^{IN}, \quad \forall t, s, s': \quad \left(\rho_{t,s}^{DA} = \rho_{t,s'}^{DA}, \quad \forall t\right) \text{ and } Pw_{\tau,s} = Pw_{\tau,s'}, \quad \forall \tau = 1,2, \dots, NH_1 \tag{3.49}$$

where NH_1 is the number of time periods between the DA and intraday markets closing time.

3.3.11 WPA Model

In this section, the bidding strategy of the WPA is formulated for profit maximization. Three electricity markets, including DA, intraday, and balancing markets, are considered in this model, as shown in Fig. 3.1 [81]. As can be seen in Fig. 3.1, the intraday market remains two and a half hours before the balancing market. With regard to the three mentioned electricity markets and considering the CVaR to control the financial risks, the objective function $\mathcal{Z}_{Obj}^{WPA}$ of the optimization problem $\text{Max}_{\Theta w_{t,s};\varphi_s,\forall s;\theta}\left[\mathcal{Z}_{Obj}^{WPA}\right]$ can be written as (3.50) [81]. Note that the time interval d_t is considered to be 1 hour and removed from the formulations.

$$\left[\mathcal{Z}_{Obj}^{WPA}\right] = \sum_{s=1}^{N_S}\sum_{t=1}^{N_T}\pi_s\left[\rho_{t,s}^{DA}.Pw_{t,s}^{DA} + \rho_{t,s}^{IN}.Pw_{t,s}^{IN} + \rho_{t,s}^{DA}.\eta_{t,s}^{+}.\varepsilon w_{t,s}^{+} - \rho_{t,s}^{DA}.\eta_{t,s}^{-}.\varepsilon w_{t,s}^{-}\right] + \zeta\left(\theta - \frac{1}{(1-\sigma)}\sum_{s=1}^{N_S}\pi_s\varphi_s\right) \tag{3.50}$$

where $\Theta w_{t,s} = [\, Pw_{t,s}^{DA},\ Pw_{t,s}^{IN},\ Pw_{t,s}^{SC},\ \varepsilon w_{t,s}^{+},\ \varepsilon w_{t,s}^{-},\quad \forall t,\ \forall s]$ are the variables related to the WPA optimization problem. The objective function is composed of the expected profit of WPA, and the CVaR, which is multiplied by the risk-aversion factor ζ. The total revenue/cost of WPA comes from the following: firstly, selling energy in the DA market; secondly, selling/purchasing energy in the intraday market and thirdly, the revenue/cost of participation in the balancing market due to positive/negative scheduling deviations from the actual generated power of producer. In (3.50), the terms $\rho_{t,s}^{DA}.\,Pw_{t,s}^{DA}$ and $\rho_{t,s}^{IN}.\,Pw_{t,s}^{IN}$ state the revenue from DA market and revenue/cost from the intraday market, respectively; while the terms $\rho_{t,s}^{DA}.\,\eta_{t,s}^{+}.\,\varepsilon w_{t,s}^{+}$ and $\rho_{t,s}^{DA}.\,\eta_{t,s}^{-}.\,\varepsilon w_{t,s}^{-}$ indicate the revenue/cost from the positive/negative energy deviations in the balancing market. The last term in (3.50) is related to considering the CVaR to control the financial risks.

The objective function of profit maximization of WPA in (3.50) is subject to some important constraints as follows [81]:

$$0 \le Pw_{t,s}^{\beta} \le Pw^{Max} \quad \forall t, \forall s, \beta = DA, SC \tag{3.51}$$

$$|Pw_{t,s}^{IN}| \le \Lambda.\, Pw_{t,s}^{DA} \quad \forall t, \forall s \tag{3.52}$$

$$Pw_{t,s}^{SC} = Pw_{t,s}^{DA} + Pw_{t,s}^{IN} \quad \forall t, \forall s \tag{3.53}$$

where (3.51) limits the offering power of WPA to the DA market and its scheduled power. Note that $Pw_{t,s}^{DA}$ and $Pw_{t,s}^{SC}$ in (3.51) can only be positive values. In other words, WPA can only sell electricity to the DA market and have a positive value for its scheduled power. The amount of WPA power to participate in the intraday market is also limited to an upper bound, which equals Λ (a bounding factor for biddings to intraday market) multiplied by its participation capacity to the DA market as formulated in (3.52). The total scheduled powers of WPA is also limited to its participation in DA and intraday offers, as formulated in (3.53) [81].

$$\varepsilon w_{\mathrm{t,s}} = Pw_{t,s} - Pw_{t,s}^{SC} \quad \forall t, \forall s \tag{3.54}$$

$$\varepsilon w_{t,s} = \varepsilon w_{t,s}^{+} - \varepsilon w_{t,s}^{-} \quad \forall t, \forall s \tag{3.55}$$

$$0 \leq \varepsilon w_{t,s}^{+} \leq Pw_{t,s} \quad \forall t, \forall s \tag{3.56}$$

$$0 \leq \varepsilon w_{t,s}^{-} \leq Pw^{max} \quad \forall t, \forall s \tag{3.57}$$

$$-\sum_{t=1}^{N_T}\left[\rho_{t,s}^{DA}.Pw_{t,s}^{DA} + \rho_{t,s}^{IN}.Pw_{t,s}^{IN} + \rho_{t,s}^{DA}.\eta_{t,s}^{+}.\varepsilon w_{t,s}^{+} - \rho_{t,s}^{DA}.\eta_{t,s}^{-}.\varepsilon w_{t,s}^{-}\right] + \theta - \varphi_s \leq 0 \quad \forall s \tag{3.58}$$

$$\varphi_s \geq 0 \quad \forall s \tag{3.59}$$

$$\left(Pw_{t,s}^{DA} - Pw_{t,s'}^{DA}\right).\left(\rho_{t,s}^{DA} - \rho_{t,s'}^{DA}\right) \geq 0 \quad \forall t, \forall s, \forall s' \tag{3.60}$$

$$Pw_{t,s}^{DA} = Pw_{t,s'}^{DA} \quad \forall t, \forall s, \forall s' : \rho_{t,s}^{DA} = \rho_{t,s'}^{DA} \tag{3.61}$$

The total negative and positive imbalances according to the amount of scheduled and actual wind power productions are formulated in (3.54)-(3.57). Constraints (3.58) and (3.59) formulate the required limitations for the CVaR calculation. (3.60) and (3.61) are used to offer non-decreasing curves to the DA electricity market.

3.4 CAES Aggregator Modeling

In this section, a bidding strategy for a CAES aggregator to participate in the electricity markets is modeled as a stochastic optimization problem, in which the goal is to maximize the profit which includes the total profits of the CAES aggregator from the electricity markets minus its operational costs. From the reliability point of view, CAES has very reliable performance and output in comparison with other producers like WPA [90]. Therefore, there is no need for CAES aggregator to participate in the balancing market. In this case, two electricity markets, including DA and intraday, are considered in this chapter for the modeling of CAES aggregator. With the two mentioned electricity markets model, the CAES operational cost, and considering the CVaR to control the financial risks, the objective function $\mathcal{Z}_{Obj}^{CAES}$ of the optimization problem $\text{Max}_{\Theta c_{t,s};\varphi_s,\forall s;\theta}\left[\mathcal{Z}_{Obj}^{CAES}\right]$ can be written as follows in (3.62):

$$\left[\mathcal{Z}_{Obj}^{CAES}\right] = \sum_{s=1}^{N_S}\sum_{t=1}^{N_T}\pi_s\left[\rho_{t,s}^{DA}.Pc_{t,s}^{DA} + \rho_{t,s}^{IN}.Pc_{t,s}^{IN} - OC_{t,s}\right] + \zeta\left(\theta - \frac{1}{(1-\sigma)}\sum_{s=1}^{N_S}\pi_s\varphi_s\right) \quad (3.62)$$

where $\Theta c_{t,s} = \left\{\begin{matrix} Pc_{t,s}^{DA},\ Pc_{t,s}^{IN},\ Pc_{t,s}^{SC},\ Pc_{t,s}^{SC,Dis},\ Pc_{t,s}^{SC,Sim}, Pc_{t,s}^{SC,Cha}, Uc_{t,s}^{SC,Dis},\ Uc_{t,s}^{SC,Sim}, \\ Uc_{t,s}^{SC,Cha},\ Ec_{t,s}^{SC},\quad \forall t,\ \forall s \end{matrix}\right\}$ are the variables of the CAES aggregator optimization problem. The objective function has two general terms, including the expected profit of CAES aggregator, which is the difference between its revenue and operating cost, and the CVaR (multiplied by the risk-aversion factor ζ). The revenue/cost of CAES aggregator is obtained from selling energy in DA and intraday markets, while its costs are the sum of the purchased energy to charge the air cavern plus variable costs of simple-cycle mode. The terms $\rho_{t,s}^{DA}.Pc_{t,s}^{DA}$ and $\rho_{t,s}^{IN}.Pc_{t,s}^{IN}$ express the revenue/cost from the selling/purchasing of energy in CAES in DA and intraday markets, respectively. The term $OC_{t,s}$ in the objective function is related to the CAES operational cost which is computed according to the different CAES operating modes (charging, discharging and simple-cycle modes) and their amount of power. The last term is for modeling of the CVaR, and it is multiplied by ζ (risk-aversion factor) The CVaR signifies the expected profit of the $(1-\sigma)\times 100$ percent of scenarios yielding the lowest profits, and it is used to regulate the risk due to profit variability confronted by the CAES aggregator. σ is the confidence level with $\sigma \in (0,1)$. Note that θ is an auxiliary variable, and its value is simultaneously optimized along with variables $\Theta c_{t,s}$ and φ_s, where φ_s is a continuous non-negative variable equal to the maximum of $\theta - \sum_{t=1}^{N_T}\left[\rho_{t,s}^{DA}.Pc_{t,s}^{DA} + \rho_{t,s}^{IN}\,Pc_{t,s}^{IN} - OC_{t,s}\right]$ and 0.

The objective function defined in (3.62) is subject to the following constraints [90]:

$$-Pc_{Com}^{Max} \le Pc_{t,s}^{\beta} \le Pc_{Exp}^{Max} \quad \forall t, \forall s, \beta = DA, SC \tag{3.63}$$

$$-\Lambda.Pc_{Com}^{Max} \le Pc_{t,s}^{IN} \le \Lambda.Pc_{Exp}^{Max} \quad \forall t, \forall s \tag{3.64}$$

$$Pc_{t,s}^{SC} = Pc_{t,s}^{DA} + Pc_{t,s}^{IN} \quad \forall t, \forall s \tag{3.65}$$

$$Pc_{t,s}^{SC} = Pc_{t,s}^{SC,Dis} + Pc_{t,s}^{SC,Sim} - Pc_{t,s}^{SC,Cha} \quad \forall t, \forall s \tag{3.66}$$

$$0 \le Pc_{t,s}^{SC,\varpi} \le Pc_{Exp}^{Max}.Uc_{t,s}^{SC,\varpi} \quad \forall t, \forall s, \varpi = Dis, Sim, Cha \tag{3.67}$$

$$Uc_{t,s}^{SC,Dis} + Uc_{t,s}^{SC,Sim} + Uc_{t,s}^{SC,Cha} \le 1 \;\; \forall t, \forall s \tag{3.68}$$

$$Ec_{t,s}^{SC} = Ec_{t-1,s}^{SC} + Er\left(Pc_{t,s}^{SC,Cha} - Pc_{t,s}^{SC,Dis}\right) \quad \forall t > 1, \forall s \tag{3.69}$$

$$Ec_{1,s}^{SC} = Ec^{INT} \quad \forall s \tag{3.70}$$

$$Ec^{Min} \le Ec_{t,s}^{SC} \le Ec^{Max} \quad \forall t, \forall s \tag{3.71}$$

$$\begin{aligned} OC_{t,s} = {} & Pc_{t,s}^{SC,Dis}\left(Hc^{Dis}.NG + Vc^{Exp}\right) + Pc_{t,s}^{SC,Sim}\left(Hc^{Sim}.NG + Vc^{Exp} + Vc^{Com}\right) \\ & + Pc_{t,s}^{SC,Cha} Vc^{Com} \quad \forall t, \forall s \end{aligned} \tag{3.72}$$

$$-\sum_{t=1}^{N_T}\left[\rho_{t,s}^{DA}.Pc_{t,s}^{DA} + \rho_{t,s}^{IN}\,Pc_{t,s}^{IN} - OC_{t,s}\right] + \theta - \varphi_s \le 0 \quad \forall s \tag{3.73}$$

$$\varphi_s \geq 0 \quad \forall s \tag{3.74}$$

$$\left(Pc_{t,s}^{DA} - Pc_{t,s'}^{DA}\right).\left(\rho_{t,s}^{DA} - \rho_{t,s'}^{DA}\right) \geq 0 \quad \forall t, \forall s, \forall s' \tag{3.75}$$

$$Pc_{t,s}^{DA} = Pc_{t,s'}^{DA} \quad \forall t, \forall s, \forall s' : \rho_{t,s}^{DA} = \rho_{t,s'}^{DA} \tag{3.76}$$

where (3.63) limits the offering CAES power to the DA market and its scheduled power, respectively, where Pc is the power related to CAES. $Pc_{Exp/Com}^{Max}$ is the maximum expanding/compressing capacity of CAES. Note that both of $Pc_{t,s}^{DA}$ and $Pc_{t,s}^{SC}$ in (3.63) in each hour can be positive or negative, which means that the CAES aggregator has the capability of either buying or selling energy in each hour of the day. The amount of CAES aggregator power to participate in the intraday market is also limited to Λ times its participation capacity to the DA market as formulated in (3.64). In other words, according to (3.64), CAES is not allowed to use its full capacity to participate in the intraday market, even it is more economical [100]. The total scheduled CAES power, which is based on the summation of CAES bidding powers to DA and intraday electricity markets, is expressed in (3.65). Eq. (3.66) shows that the CAES scheduled power is based on three CAES working modes (*i.e.,* discharging (*superscript Dis*), simple-cycle (*superscript Sim*) or charging (*superscript Cha*) modes). The restrictions of CAES power in these modes are formulated in (3.67), where Uc is the binary variable related to the ON/OFF operating status of CAES. It is worthwhile to mention that at each period and scenario, the CAES can only work in one of the charging, discharging, or simple-cycle modes. This limitation can be precisely specified in (3.68). The scheduled CAES energy level, which is also called the state-transition equation, is expressed in (3.69), where Er is the CAES energy ratio for converting power to energy in cthe avern and Ec is the energy level related to the CAES. The initial value (Ec^{INT}) of this energy is limited by (3.70). This energy is also restricted by the capacity of CAES cavern as mathematically formulated in (3.71), where $Ec^{Max/Min}$ is the maximum/minimum schedulable level of energy in CAES cavern. Eq. (3.72) formulates the operational cost of CAES, which is used in the objective function (3.62), where Hc stands for the CEAS heat rate in one of the operating modes, *NG* is the natural gas price and $Vc^{Exp/Com}$ is the CAES variable operation and maintenance cost for expanding/compressing modes. The CAES operational cost is computed according to the different CAES operating modes (charging, discharging and simple-cycle modes) and their amount of power. In order to calculate and control the functional risk, (3.73) and (3.74) are required for the model. The stochastic programming model (3.62)–(3.74) can be solved to attain the optimal quantities to be submitted in the DA market. However, it is more appropriate to develop optimal offering curves for every hour of this market. For this purpose, variable Pc_t^{DA}, which are the power traded in the DA market for each time period *t,* is considered to be dependent on scenarios ($Pc_t^{DA} \rightarrow Pc_{t,s}^{DA}$) and the constraints (3.75) and (3.76) are added to the model (3.62)–(3.74). Constraints (3.75) make offering curves non-decreasing, which is an obligation in most electricity markets. Eqs. (3.76) are non-anticipativity constraints, which enforce the idea that only one offering curve can be submitted to the DA market regardless of the imbalance price and actual wind power generation. Note that the bidding strategy model remains decomposable at each period, and even constraints (3.75) and (3.76) are included.

3.5 HPP Modeling

In this section, a bidding strategy for the HPP is modeled to achieve the maximum profit of the joint operation of CAES aggregator and WPA. All three electricity markets used in WPA modeling, as shown in Fig. 3.1 are also taken into consideration in HPP modeling [81]. With regards to the CVaR model, the objective function $\mathcal{Z}_{Obj}^{Hpp}$ of the optimization problem $\mathrm{Max}_{\Theta h_{t,s};\varphi_s,\forall s;\theta}\left[\mathcal{Z}_{Obj}^{Hpp}\right]$ for the participation of HPP in all given electricity markets can be written as follows:

$$\left[\mathcal{Z}_{Obj}^{Hpp}\right] = \sum_{s=1}^{N_S}\sum_{t=1}^{N_T}\pi_s\big[\rho_{t,s}^{DA}.Ph_{t,s}^{DA} + \rho_{t,s}^{IN}.Ph_{t,s}^{IN} + \rho_{t,s}^{DA}.\eta_{t,s}^{+}.\varepsilon h_{t,s}^{+} - \rho_{t,s}^{DA}.\eta_{t,s}^{-}.\varepsilon h_{t,s}^{-}$$
$$- OC_{t,s}\big] + \zeta\left(\theta - \frac{1}{(1-\sigma)}\sum_{s=1}^{N_S}\pi_s\varphi_s\right) \tag{3.77}$$

where $\Theta h_{t,s} = \{Ph_{t,s}^{DA}, Ph_{t,s}^{IN}, Ph_{t,s}^{SC}, \varepsilon h_{t,s}^{+}, \varepsilon h_{t,s}^{-}, Pw_{t,s}^{DA}, Pc_{t,s}^{DA}, Pw_{t\omega}^{IN}, Pc_{t,s}^{IN}, Pw_{t,s}^{SC}, Pc_{t,s}^{SC}, Pc_{t,s}^{SC,Dis}, Pc_{t,s}^{SC,Sim}, Pc_{t,s}^{SC,Cha}, Uc_{t,s}^{SC,Dis}, Uc_{t,s}^{SC,Sim}, Uc_{t,s}^{SC,Cha}, Ec_{t,s}^{SC} \quad \forall t, \forall s\}$ are the variables related to the HPP optimization problem. As can be seen from (3.77), two general expressions of the objective function are included, the expected profit of HPP (i.e., as the result of market transactions and operational cost) and the CVaR. The revenue/cost of HPP comes from selling/purchasing energy in both of the DA and intraday markets as well as the revenue/cost from the positive/negative energy deviations in the balancing market. In (3.77), the terms $\rho_{t,s}^{DA}.Ph_{t,s}^{DA}$ and $\rho_{t,s}^{IN}.Ph_{t,s}^{IN}$ refer to the revenue/cost of HPP from the DA and intraday markets, and the terms $\rho_{t,s}^{DA}.\eta_{t,s}^{+}.\varepsilon h_{t,s}^{+}$ and $\rho_{t,s}^{DA}.\eta_{t,s}^{-}.\varepsilon h_{t,s}^{-}$ indicate the revenue/cost from the positive/negative energy deviations in the balancing market. The term $OC_{t,s}$ in the objective function is related to the CAES operational cost which is computed according to the different CAES operating modes (charging, discharging and simple-cycle modes) and their amount of power; see (3.72). The last term in the HPP modeling objective function is for modeling of the CVaR which is multiplied by the risk-aversion factor ζ.

The objective function of the HPP optimization problem (3.77) is subject to some joint constraints associated with both of the WPA and CAES providers, some constraints associated specifically with for modeling of CAES aggregator, and some only for the WPA model.

The constraints of HPP associated with the CAES model are defined previously in the CAES modeling section; see (3.63)-(3.72). The constraints of HPP associated specifically with the WPA model are also previously defined in the WPA modeling section; see (3.51)-(3.57).

The joint constraints associated with both of the WPA and CAES providers to function as an HPP are defined as bellow:

$$Ph_{t,s}^{\beta} = Pw_{t,s}^{\beta} + Pc_{t,s}^{\beta} \quad \forall t, \forall s, \beta = DA, SC, IN \tag{3.78}$$

$$Ph_{t,s}^{SC} = Ph_{t,s}^{DA} + Ph_{t,s}^{IN} \quad \forall t, \forall s \tag{3.79}$$

$$\varepsilon h_{t,s} = Pw_{t,s} + Pc_{t,s} - Ph_{t,s}^{SC} \quad \forall t, \forall s \tag{3.80}$$

$$\varepsilon h_{t,s} = \varepsilon h_{t,s}^{+} - \varepsilon h_{t,s}^{-} \quad \forall t, \forall s \tag{3.81}$$

$$0 \le \varepsilon h_{t,s}^{+} \le Pw_{t,s} + Pc_{t,s} \quad \forall t, \forall s \tag{3.82}$$

$$0 \le \varepsilon h_{t,s}^{-} \le Pw^{Max} + Pc_{Exp}^{Max} \quad \forall t, \forall s \tag{3.83}$$

$$-\sum_{t=1}^{N_T}\left[\rho_{t,s}^{DA}.Ph_{t,s}^{DA}+\rho_{t,s}^{IN}\,Ph_{t,s}^{IN}+\rho_{t,s}^{DA}.\eta_{t,s}^{+}.\varepsilon h_{t,s}^{+}-\rho_{t,s}^{DA}.\eta_{t,s}^{-}.\varepsilon h_{t,s}^{-}\right]+\ \theta-\varphi_s$$

$$\leq 0 \quad \forall s \tag{3.84}$$

$$\varphi_s \geq 0 \quad \forall s \tag{3.85}$$

$$\left(Ph_{t,s}^{DA}-Ph_{t,s'}^{DA}\right).\left(\rho_{t,s}^{DA}-\ \rho_{t,s'}^{DA}\right)\geq 0 \quad \forall t,\forall s,\forall s' \tag{3.86}$$

$$Ph_{t,s}^{\mathrm{DA}}=Ph_{t,s'}^{\mathrm{DA}} \quad \forall t,\forall s,\forall s' :\ \rho_{t,s}^{DA}=\ \rho_{t,s'}^{DA} \tag{3.87}$$

where (3.78) limits DA and intraday offers and the total scheduled power of HPP. The total scheduled power of HPP includes its DA and intraday offers formulated in (3.79). The total negative and positive imbalances according to the HPP scheduled power and the actual wind and CAES powers at the time of balancing market are formulated in (3.80) to (3.83). As previously mentioned, unlike the WPA, the CAES aggregator is very reliable and has a deterministic output. For that reason, in this chapter, it is supposed that the actual CAES powers at the time of balancing market are equal to its power that has been scheduled. Similar to WPA and CAES modeling, constraints (3.84) and (3.85) are formulated for CVaR calculation, and (3.86) and (3.87) are defined for obtaining the non-decreasing DA market offering curves.

3.6 Wind Generation and Market Prices Modeling

The wind power and market price uncertainties are modeled as follows: N_1, N_2, N_3 and N_4 scenarios are generated for wind power generation, DA market, intraday market and balancing market prices, respectively.

These uncertainty sources are separated into two categories; 1) wind power generation ($Pw(w)$) and DA market price $\rho^{DA}(d)$ which are independent uncertainty parameters (*here-*

and-now), 2) the intraday market prices $\rho^{IN}(d,i)$ which are feasible for each possible realization of DA market price scenarios. In other words, the intraday market price scenarios are generated based on DA market price scenarios. Similarly, the balancing market price $(\eta^{+}(b), \eta^{-}(b))$ scenarios are generated based on each possible wind power generation scenarios, DA market, and intraday market price scenarios.

Due to the dependency of intraday and balancing market prices on wind power generation and DA market price, the correlation among these stochastic variables is defined as $(\rho^{DA} - \rho^{IN})$ and $(\eta^{+} + \eta^{-} - 1)$ for all scenarios. Also, the symmetric scenario tree is implemented to construct the $N_S = N_1 \times N_2 \times N_3 \times N_4$ scenarios based on the independent and dependent scenarios.

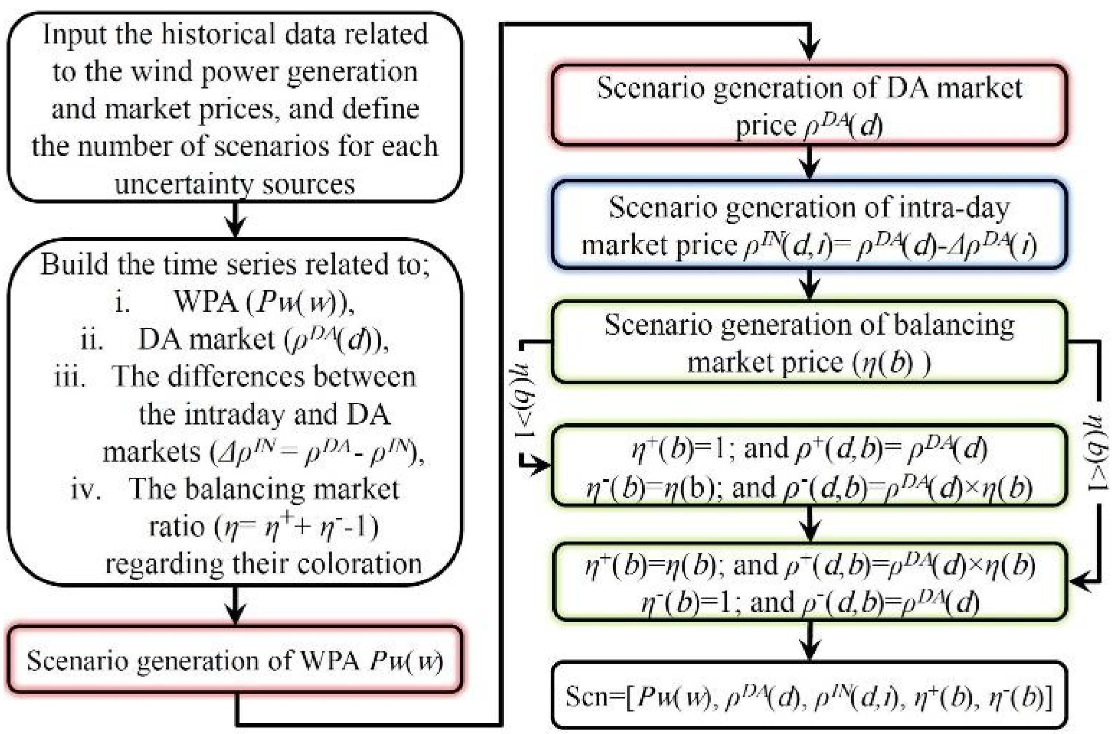


Fig. 3.6 Flowchart of the stochastic variable modeling process

Fig. 3.6 shows the flowchart of the stochastic modeling process which leads to the generation of all scenarios $(Pw(w), \rho^{DA}(d), \rho^{IN}(d,i), \eta^{+}(b),\ \eta^{-}(b))$. It is worthy to mention that the red highlighted sections indicate the first category (i.e., the wind power generation and DA market price scenarios), and the blue and green highlighted sections indicate the second category (i.e., the intraday and balancing market price scenarios). After scenario generation of balancing market prices $\eta(b)$, the highlighted green color parts of Fig. 3.6 show that there are two ways of calculating the balancing market prices $(\eta^{+}(b), \eta^{-}(b))$ based on the values of $\eta(b)$.

The uncertainties of wind power and market prices are produced with a set of scenarios using an adapted hybrid neural network and a hybrid Jaya algorithm [134]. Jaya algorithm [135] is a new simple and efficient algorithm. Similar to the other algorithms, it only has the common parameters that will be determined by the user like population number and iterations of an algorithm without the need of any specific control parameters that would be determined by the user. This algorithm is based on the best and the worst candidate solutions in the iterations [135]. It has good feasibility and performance in solving different engineering optimization problems such as complex constrained design optimization [136], dimensional optimization of a micro-channel heat sink [135], and surface grinding process optimization [137]. An efficient improved hybrid Jaya algorithm based on time-varying acceleration coefficients (TVAC) and learning phase introduced in teaching-learning-based optimization (TLBO), named LJaya-TVAC algorithm along with an adapted hybrid neural network is proposed to produce the uncertainties of wind power and market prices. The search power of the proposed LJaya-TVAC algorithm for finding the optimal solutions is firstly tested on the standard real-parameter uni-modal and multi-model functions with the dimension of 30 to 100 and then tested on various types of nonlinear mixed-integer reliability–redundancy allocation problems (RRAPs). The results are compared with the original Jaya algorithm and best results reported in the recent literature. The obtained optimal results of the proposed LJaya-TVAC algorithm provide evidence for the better and acceptable optimization performance compared to the original Jaya algorithm and other reported optimal results.

3.6.1 Jaya algorithm

Jaya algorithm is a recently proposed algorithm which is a powerful and simple optimizer for real-world optimization problems. The original flowchart of the optimization process for Jaya algorithm is shown in Fig. 3.7 [135]. In the Jaya algorithm, each member of all population (*N*), has its location (solution) in the i^{th} iteration (i = 1:i_{max}) of the algorithm. X_k^i (k =1: N) is defined by the optimization problem parameters in the d-dimensional solution search space: $X_k^i = [X_{1,k}^i, X_{2,k}^i, \dots, X_{d,k}^i]$. The new location value $X_k^{i+1} = [X_{1,k}^{i+1}, X_{2,k}^{i+1}, \dots, X_{d,k}^{i+1}]$ for the k^{th} member X_k^i is achieved by updating the locations iteratively. If $f(X_k^{i+1}) \leq f(X_k^i)$, where $f(\cdot)$ is the evaluation function, the new location value (X_k^{i+1}) replaces the old location value (X_k^i) using the following equation [135]:

$$X_k^{i+1} = X_k^i + rand_1^i(X_{best}^i - |X_k^i|) - rand_2^i(X_{worst}^i - |X_k^i|) \tag{3.88}$$

where, $X_{best}^i = [X_{1,best}^i, X_{2,best}^i, \dots, X_{d,best}^i]$ and $X_{worst}^i = [X_{1,worst}^i, X_{2,worst}^i, \dots, X_{d,worst}^i]$ are the best and worst solutions obtained until the i^{th} iteration of the algorithm, respectively. $rand_1^i = [rand_{1,1}^i, rand_{1,2}^i, \dots, rand_{1,d}^i]$ and $rand_2^i = [rand_{2,1}^i, rand_{2,2}^i, \dots, rand_{2,d}^i]$ are two vectors of random numbers in the range [0, 1] in the i^{th} iteration of the algorithm. Also, $|X_k^i|$ is the absolute value of X_k^i.

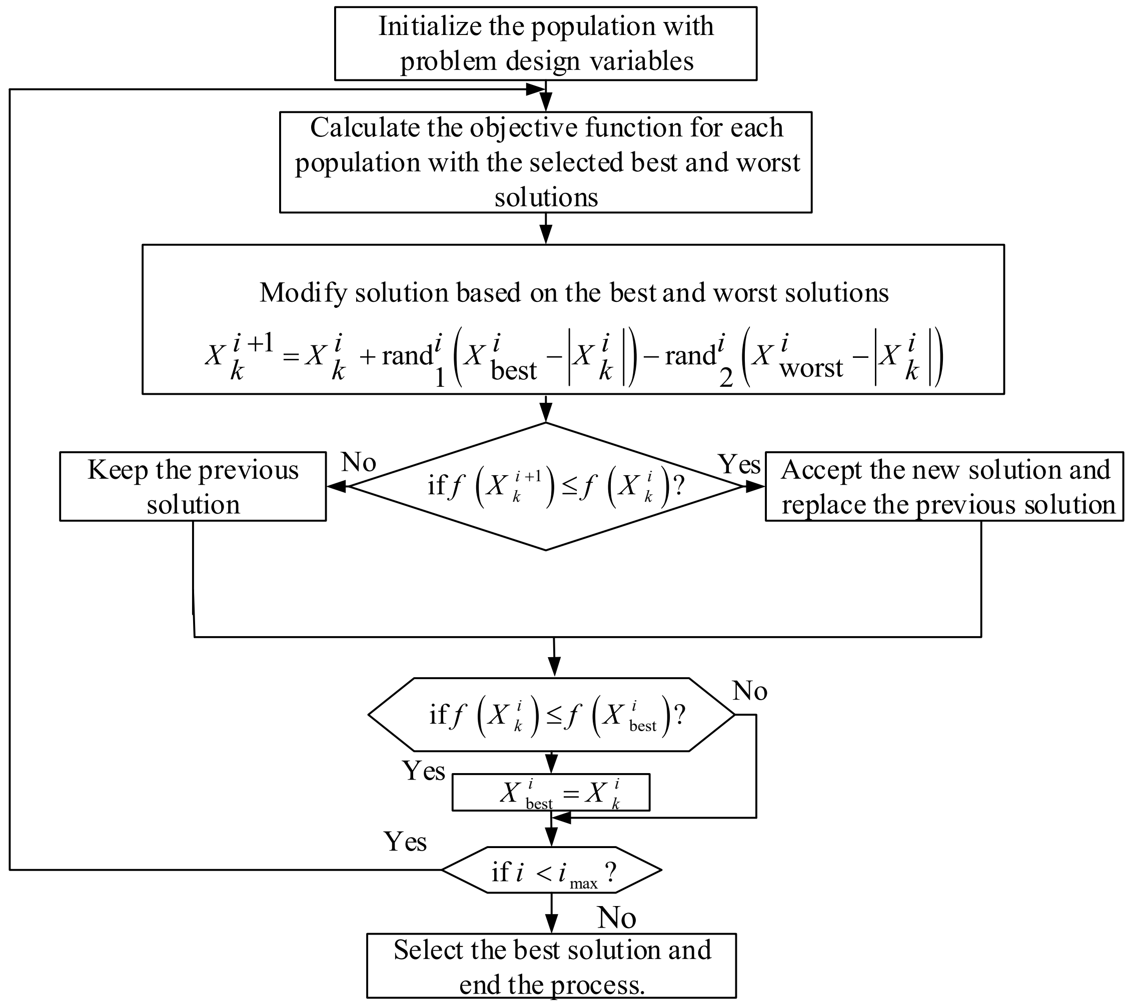


Fig. 3.7 The optimization process of the original Jaya algorithm.

3.6.2 The hybrid enhanced Jaya algorithm

In this section, the hybrid enhanced Jaya algorithm using TVAC and learning phase is presented. This algorithm increases the search power around the globally optimal solution (X_{best}) in the primary iterations for faster convergence, and also increases the search power in the latest iterations.

1) Jaya algorithm with time-varying acceleration coefficients (Jaya-TVAC)

In the first phase, two new time-varying acceleration coefficients C_1^i and C_2^i are proposed based on the method by [138] to improve the Jaya algorithm, which is called Jaya-TVAC algorithm. The new location value for X_k^i is then modified as follows:

$$X_k^{i+1} = X_k^i + C_1^i \times rand_1^i(X_{best}^i - |X_k^i|) - C_2^i \times rand_2^i(X_{worst}^i - |X_k^i|) \tag{3.89}$$

$$C_1^i = C_1^1 - \left(C_1^1 - C_1^{i_{\max}}\right)\left(\frac{i-1}{i_{\max}-1}\right) \tag{3.90}$$

$$C_2^i = C_2^{i_{\max}} - \left(C_2^{i_{\max}} - C_2^1\right)\left(\frac{i_{\max}-i}{i_{\max}-1}\right) \tag{3.91}$$

where $C_1^1 = C_2^1 = 1$ and $C_1^{i_{\max}} = 0.5$ and $C_2^{i_{\max}} = 0$ are obtained for the best values.

2) Hybrid Jaya-TVAC algorithm with learning phase (LJaya-TVAC) based on TLBO algorithm

In the second phase, a learning phase introduced in [139-141] is added to the proposed algorithm for finding the better final solutions with higher convergence rate through the increased local search of Jaya algorithm. The flowchart of the optimization process for LJaya-TVAC algorithm is shown in Fig. 3.8. The new location value X_k^{i+1} can be achieved using (3.92). Here two solution variables X_j^i (j^{th} member of the population) and X_h^i (h^{th}

member of the population) are randomly selected as shown in (3.92). If the value of the objective function for the new location value X_k^{i+1} is better than the old location value $X_k^i\left(f\left(X_k^{i+1}\right) \leq f\left(X_k^i\right)\right)$, the new location value X_k^{i+1}will replace the old location value X_k^i.

$$X_k^{i+1} = X_k^i + rand_3^i \times \begin{cases} (X_j^i - X_h^i) & if\ f\left(X_j^i\right) \leq f\left(X_h^i\right) \\ (X_h^i - X_j^i) & Otherwise \end{cases} \tag{3.92}$$

where $rand_3^i = [rand_{3,1}^i, rand_{3,2}^i, \dots, rand_{3,d}^i]$ is a vector of random numbers in the range [0, 1] in the i^{th} iteration of the algorithm.

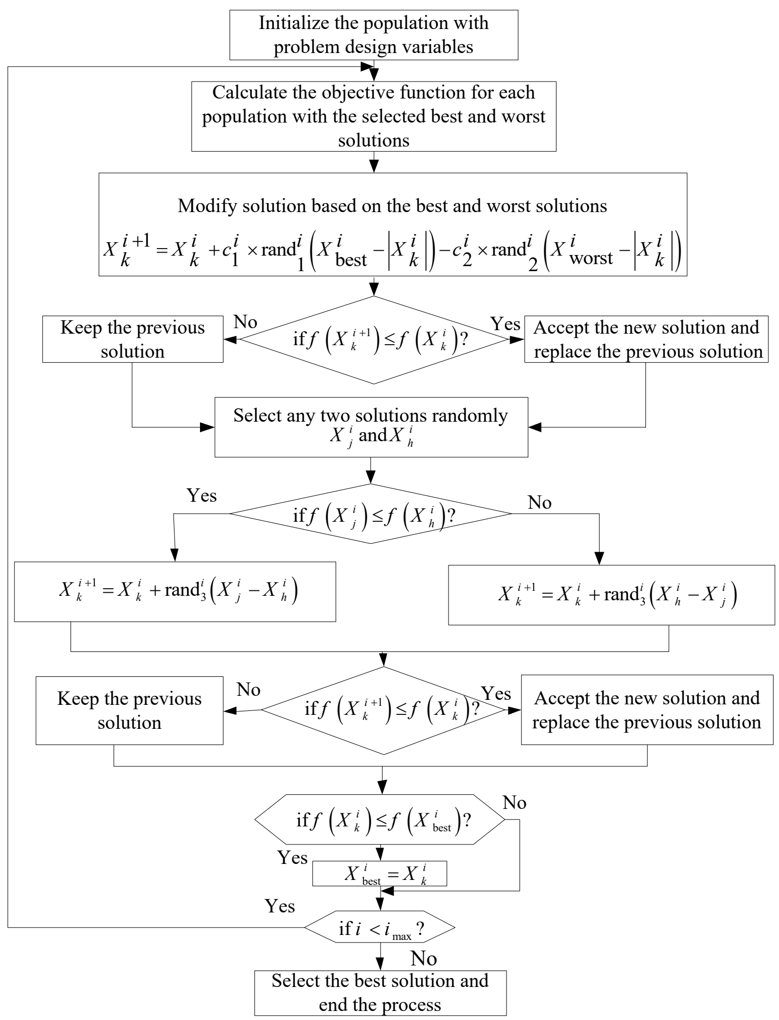


Fig. 3.8 The optimization process of LJaya-TVAC algorithm.

3) LJaya-TVAC algorithm for real-parameter problems

In order to validate the performance of the LJaya-TVAC algorithm for the real-parameter test functions, various types of real-parameter test functions are chosen [142]. The details of the sixth typical unimodal and multi-modal real-parameter test functions (*F*) that are selected to evaluate the effectiveness of the proposed algorithms are summarized as follows:

- F_1: Shifted Rotated High Conditioned Elliptic (uni-modal, non-separable and scalable test function):

  $$F_1(x) = \sum_{j=1}^{d} (10^6)^{\frac{j-1}{d-1}} {z_j}^2 \;, \qquad z = (x - o) * M, x = [x_1, x_2, \ldots, x_d]$$

  $o = [o_1, o_2, \ldots, o_d]$: the shifted global optimum and *M*: orthogonal matrix

  with $x_i \in [-100, 100]$ and $F_1(o) = 0$.

- F_2: Shifted Schwefel's Problem 1.2 with Noise in Fitness (uni-modal, non-separable and scalable test function):

  $$F_2(x) = \left(\sum_{j=1}^{d} \left(\sum_{t=1}^{j} z_t \right)^2 \right) * (1 + 0.4|N(0,1)|), \qquad z = x - o,$$

  $o = [o_1, o_2, \ldots, o_d]$: the shifted global optimum

  with $x_i \in [-100, 100]$ and $F_2(o) = 0$.

- F_3: Schwefel's Problem 2.6 with Global Optimum on Bounds (uni-modal, non-separable and scalable test function):

  $$F_3(x) = \max\{|A_j x - B_j|\}$$

  A is a *d*×*d* matrix, A_j is the j^{th} row of *A*, $B_j = A_j * o$

with $x_i \in [-100, 100]$ and $F_3(o) = 0$.

- F_4 : Shifted Rosenbrock's (multi-modal, non-separable and scalable test function):

$$F_4(x) = \sum_{j=1}^{d-1} \left(100\left(z_j^2 - z_{j+1}\right)^2 + \left(z_j - 1\right)^2\right), z = x - o + 1$$

with $x_i \in [-100, 100]$ and $F_4(o) = 0$.

- F_5: Shifted Rotated Ackley's with Global Optimum on Bounds (multi-modal, non-separable and scalable test function):

$$F_5(x) = -20exp\left(-0.2\sqrt{\tfrac{1}{d}\textstyle\sum_{j=1}^{d} z_j^2}\right) - exp\left(\tfrac{1}{d}\textstyle\sum_{j=1}^{d}\cos\left(2\pi z_j\right)\right) + 20 + e, z = x - o$$

with $x_i \in [-32.0, 32.0]$ and $F_5(o) = 0$.

- F_6: Shifted Rastrigin's (multi-modal, separable and scalable test function):

$$F_6(x) = \sum_{j=1}^{d-1}\left(z_j^2 - 10\cos\left(2\pi z_j\right) + 10\right), z = x - o$$

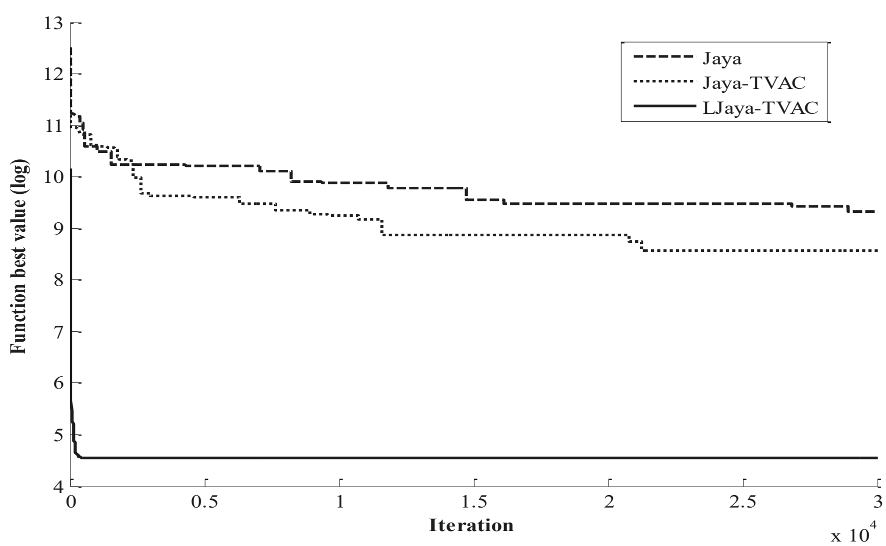
with $x_i \in [-5.0, 5.0]$ and $F_6(o) = 0$.

The Mean (mean value of the best results) and Std (standard deviation of the best results) indexes for the proposed Jaya algorithms of each real-parameter problem over 30 runs for d=30 and d=100 with i_{max} =d*1000, and the population size N=50 are given in Table 3.1. Also, Fig. 3.9 shows the convergence plots of the proposed Jaya algorithms for the real-parameter functions. The proposed LJaya-TVAC algorithm obtains better optimal results with faster convergence characteristics compared to the original Jaya and Jaya-

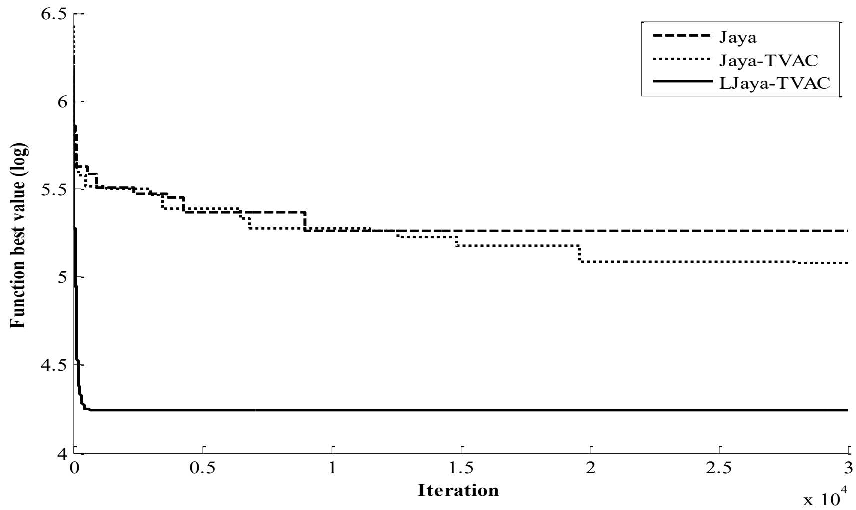
TVAC algorithms. The results show that the proposed LJaya-TVAC method is successfully implemented to the real-parameter optimization problems with different dimensions.

Table 3.1 The best results (Mean±Std) obtained from the Jaya algorithms for real-parameter problems.

F	*d*	Jaya	Rank	Jaya-TVAC	Rank	LJaya-TVAC	Rank
F_1	30	5.70e+07± 8.64e+06	3	2.91e+07±2.16e+06	2	1.93e+04±1.42e+04	1
	100	1.29e+09±1.57e+08	3	8.07e+08±1.13e+08	2	1.76e+06±6.78e+05	1
F_2	30	1.26e+04±1.27e+03	3	6.07e+03±5.32e+03	2	9.98e+01± 7.56e+01	1
	100	3.68e+05± 2.31e+04	3	4.42e+04±2.87e+04	2	2.43e+04± 1.85e+04	1
F_3	30	3.90e+03±2.45e+03	3	4.77e+02± 5.83e+02	2	1.82e+02± 1.90e+02	1
	100	3.86e+04±3.09e+03	3	1.07e+03±4.65e+03	2	9.30e+02± 2.24e+03	1
F_4	30	8.19e+07±3.82e+07	3	2.52e+07± 8.14e+06	2	3.29e+00± 3.21e+00	1
	100	5.36e+09±1.03e+09	3	1.89e+09±7.36e+08	2	2.98e+00±1.25e+00	1
F_5	30	20.871±0.083	3	20.818±0.044	2	20.72±0.061	1
	100	21.271±0.027	3	21.065±0.017	2	20.85±0.012	1
F_6	30	200.50±7.166	3	180.59±12.42	2	72.41±5.45	1
	100	896.75±69.301	3	854.71±38.59	2	464.64±26.36	1



(a)



(b)

Fig. 3.9 Convergence plots of the proposed Jaya algorithms for the real-parameter function with d=30: (a) F_2 and (b) F_6.

3.7 Case Study and Results

The intention of the presented method is to bring together a WPA and CAES producer as an HPP to contribute to three electricity markets.

The offered methodology is applied to the Sotavento (Spain) experimental wind farm, with a maximum capacity of 26.54 MW [143]. The stochastic wind power generation is modeled using the procedure presented in Section 3.6. In order to train the artificial neural network, the wind power historical data of the year 2010 are used. The scenarios related to market prices are derived by a three-step process: First, market prices are predicted for 30 days using an adapted hybrid neural network and a hybrid Jaya algorithm [81, 134], and the error probability distribution function (PDF) is estimated for each hour (i.e., 24 PDFs in this study). Next, according to the estimated PDFs, immense numbers of scenarios are generated by implementing the roulette wheel mechanism. Finally, the scenario reduction technique (the fast forward algorithm) is implemented in order to reduce the number of scenarios by eliminating similar scenarios and very low probable scenarios [144].

The historical data of market prices are also derived based on the Iberian Peninsula electricity market [145]. The uncertainties of the problem are modeled through a scenario tree with 3000 scenarios (10 × 5 × 6× 10) including ten, five, six and, ten scenarios for DA, intraday, balancing market prices and the wind generation, respectively. The simulation results are presented for the 12th of March, 2010. Note that if there are not many historical data available, some other types of methods, such as robust optimization or information gap theory, can be used to solve the optimization problem [146, 147].

The CAES heat rate for the discharging and simple-cycle mode is considered to be 0.4185 and 0.837, respectively, in which the simple-cycle mode heat rate has the doubled value. The cost of expander and compressor operation and maintenance are similarly selected to be 0.87 €/kWh. The air storage level of the cavern is limited between 1 and 15 MW. The initial air storage level of the cavern and the energy ratio of CAES are 1 MW and 0.95, respectively. Also, the natural gas price is 3.5 €/GJ.

The upper bound level of CAES and wind power production for the intraday market are similarly considered to be equal to 30 percent of their DA market production level. Also, in the CVaR calculation, the confidence level σ is given to be 0.95.

The offered methodology is initially applied to the MATLAB software to generate wind power and market price scenarios. After reducing the number of scenarios by the scenario reduction technique, the scenario data are used as an input to the GAMS software. GAMS software is a popular software for solving optimization problems. In GAMS software, we can easily and quickly formulate optimization problems using an approach that is very similar to the original algebraic notations. Although it is effortless to learn the GAMS programing language, it is powerful.

Note that the CPLEX solver is used in the GAMS software to solve the optimization problem. All the simulations of the study are performed in less than 120.756 seconds on a 2.3 GHz Intel® CORETMi5 laptop with 8 GB of RAM.

In this chapter, five cases are considered to evaluate the applicability and effectiveness of the proposed approach as follows.

3.7.1 Case I: Base Case

In the base case, the WPA and CAES producers are coordinated to participate in three electricity markets. In this case, the CAES simple-cycle mode operation is not considered by not adding it to the formulation. The offering DA market curves are also not considered by not including (3.75), (3.60) and (3.86) in the optimization problems of WPA, CAES, and HPP modeling. Moreover, the CVaR is not considered in the base case by letting the risk factor $\zeta = 0$.

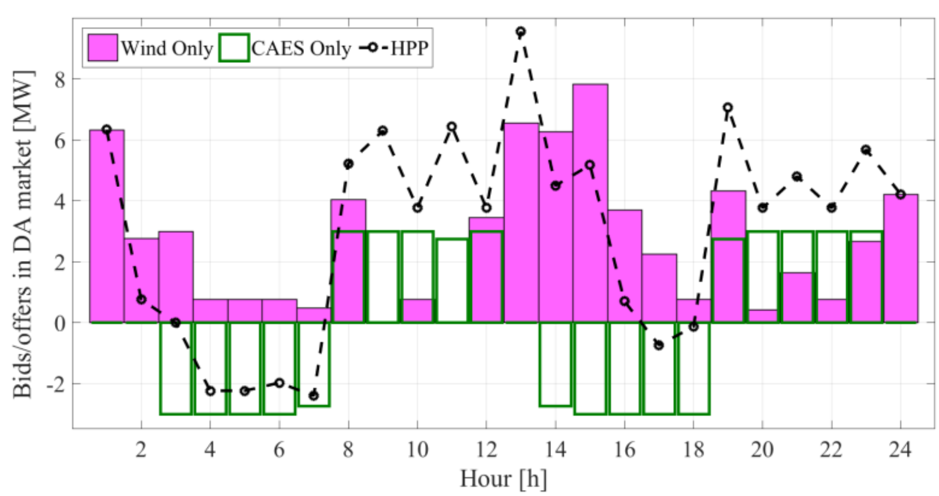


Fig. 3.10 Optimal hourly power bids for the DA market

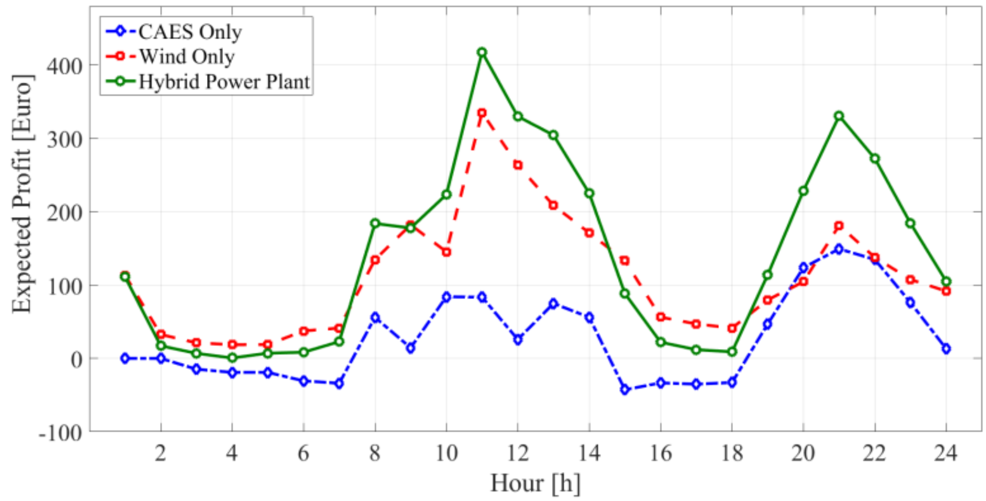


Fig. 3.11 Hourly expected profit of CAES, WPA and HPP

Fig. 3.10 depicts the comparison of optimal energy hourly bids in the DA market for three different configurations including WPA only, CAES aggregator only, and HPP. It can be seen that more capacity of CAES for storage is exploited during the period of off-peak when it joins with WPA, and subsequently this stored energy can be released during the peak periods. Obviously, more flexibility of production can be offered by having an HPP comparing to two independent aggregators to provide energy during specific peak periods. Hourly expected profit of operation for three given configurations is compared in Fig. 3.11. Noteworthily, WPA can offer higher hourly profit than HPP is some periods (e.g., hours 2 - 7). It can be deduced that the CAES initially attempts to entirely exploit the wind power to store energy in its cavern, and then charges the remaining capacity by buying energy from the markets. On the contrary, the hourly profit of HPP is superior to WPA in some periods (e.g. hours 19 - 24) as the result of simultaneous utilization of WPA and CAES.

3.7.2 Case II: Considering Bidding Curve

CAES aggregator and the WPA are incorporated in this case study to participate in different markets regarding bidding curves. None of the financial risk factor and simple-cycle mode of CAES are considered in this section. It means that the risk factor ζ=0; while the formulations related to CAES simple-cycle mode are not modeled in the market formulation. However, bidding curves equations (3.75), (3.60) and (3.86) are incorporated in the optimization.

The optimal charging/discharging pattern of CAES aggregator for each scenario of participating HPP in the DA market is shown in Fig. 3.12.

It can be inferred that the opportunity for adoption of different patterns is available for CAES to tackle scenarios which model fluctuations of DA market price.

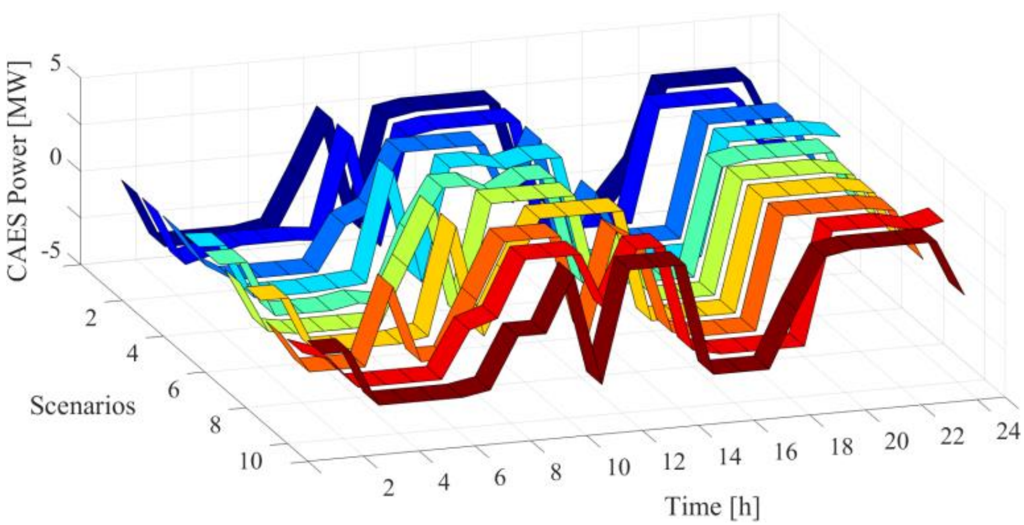


Fig. 3.12 Optimal charging/discharging pattern of CAES.

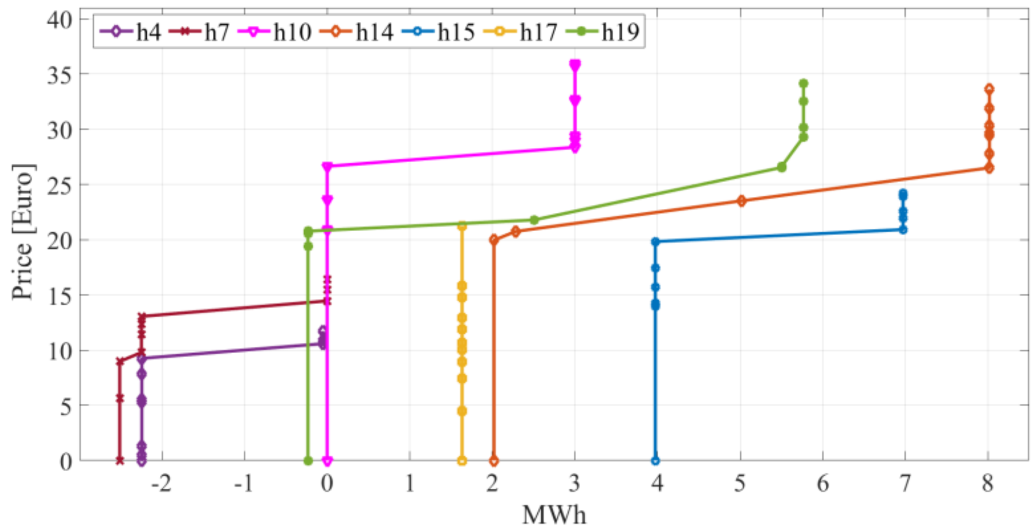


Fig. 3.13 HPP bidding curves for DA market

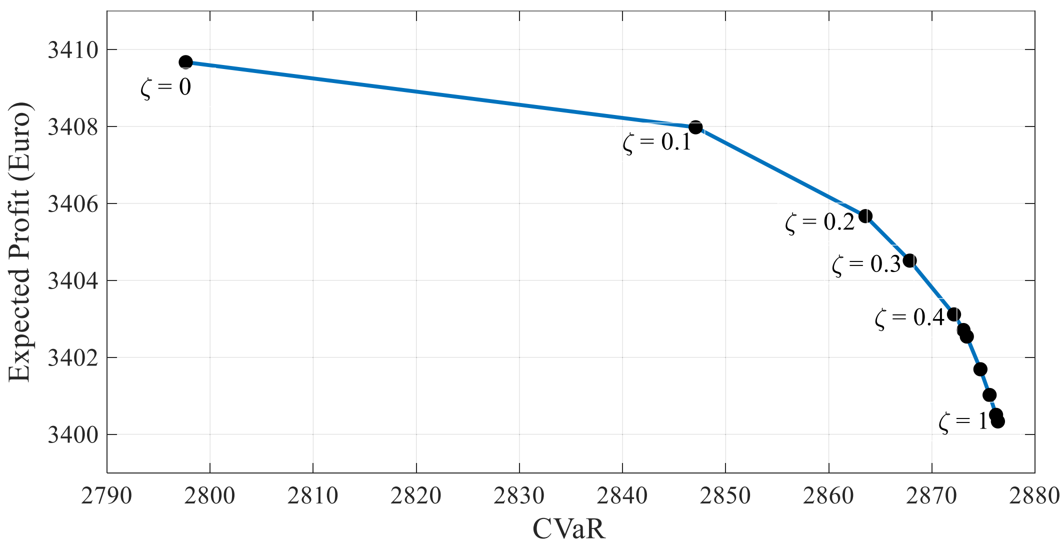


Fig. 3.14 Expected profit versus CVaR for different values of ζ: efficient frontier

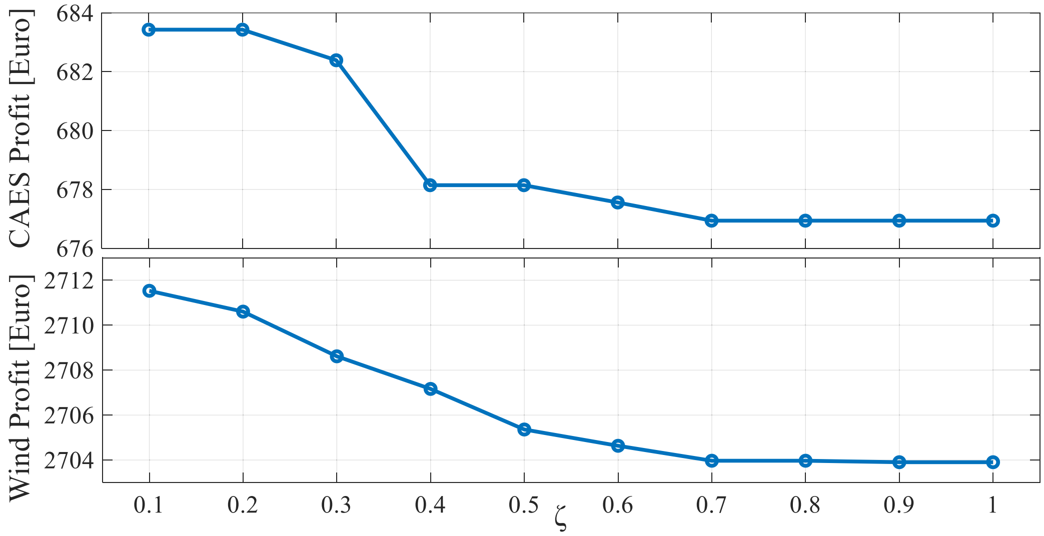


Fig. 3.15 Profit comparison for CAES and WPA versus different ζ values

As illustrations, bidding curves corresponding to some hours (i.e., 4, 7, 10, 14, 15, 17 and 19) of DA market are shown in Fig. 3.13. It is noticeable in the power curve that HPP bids zero at hour 10 for the prices less than €27, while less than zero are bid for all prices at hour 4, which means HPP tends to only buy power from the DA market. In fact, the same pattern can be seen for hours 4 and 7 though zero-power is offered for the prices more than €15. Two pattern types can be seen in the bidding curve related to hour 19. For this specific hour, there are buying the power in terms of prices less than €21 and selling for prices more than €21. It should be mentioned that HPP tends to sell energy to the market for curves corresponding to hours 14, 15, and 17. Straight line for offering curve of hour 17 means that the same amount of power is offered to the market by the HPP for all prices.

3.7.3 Case III: Considering Financial Risk

The coordination of CAES aggregator and WPA for participation in three mentioned markets is considered in this section while financial risk and bidding curves are considered.

Modeling of the simple-cycle mode of CAES is not included in this case. Eqs. (3.75), (3.60) and (3.86) are involved in the formulation of markets as similar to Case II. Fig. 3.14 depicts the efficient frontier that is the expected profit contrasted with the CVaR for different values of ζ. The optimal solution achieved for $\zeta = 0$ reaches the maximum expected profit and the maximum risk. The expected profit ranges from €3409.7 for $\zeta = 0$ to €3400.3 for $\zeta = 1$, respectively. As can be seen from Fig. 3.14, a decrease of 0.2738% in the expected profit produces 2.8153% increase in the CVaR. It is worth mentioning that a small amount of the expected profit deviation and a large amount of the CVaR specify a risk-averse solution. Also, low-risk solutions are those with high CVaR and low expected profits. The patterns of profit change for configurations of WPA only and CAES only versus variations of ζ are shown in Fig. 3.15. The expected profit of HPP as well as its difference from the combined profit of independent WPA and CAES operations as a function of ζ is shown in Fig. 3.16. As can be deduced from Fig. 3.15 and Fig. 3.16, there are profit reductions for all configurations with the increase in the value of the risk factor ζ. Such decreases can be manifested as a reasonable and expectable phenomenon as the result of a decrease in the amount of financial risk. However, the HPP extra profit increases along with the growth of ζ value. In other words, more profit is attained even when the financial risk is considered in the joint operating model. This increase in the HPP extra profit even with the growth of ζ value, which demonstrates the robustness of the proposed joint configuration. Please note that the HPP extra profit is equal to the profit of the HPP minus the summation of the WPA and CAES aggregator profits. It is noteworthy that the minimum and maximum extra profits are achieved at the risk factors $\zeta = 0.2$ and $\zeta = 0.7$. Note that the limit for variation of the risk factor ζ in Fig. 3.14 to Fig. 3.16 is [0.1, 1].

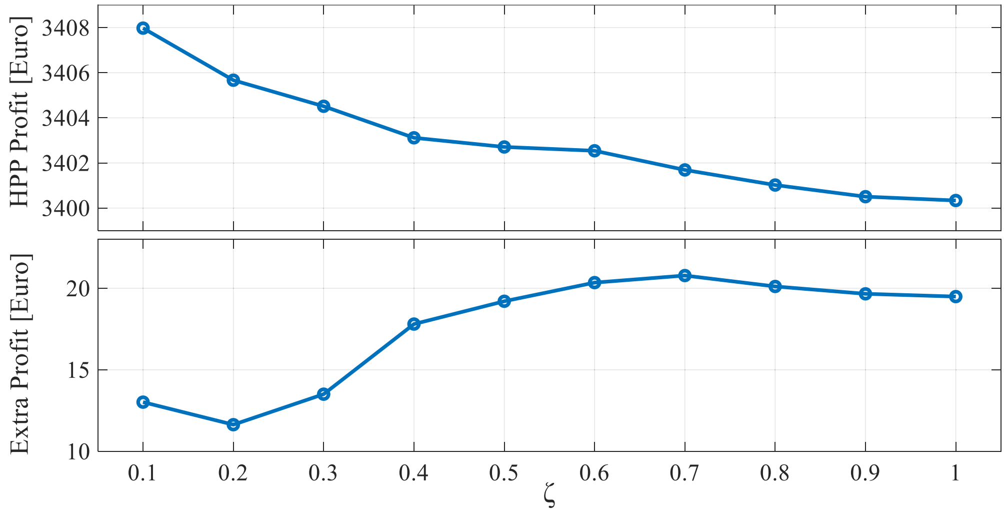


Fig. 3.16 HPP profit and its extra profit compared with the summation of independent operations versus different ζ values

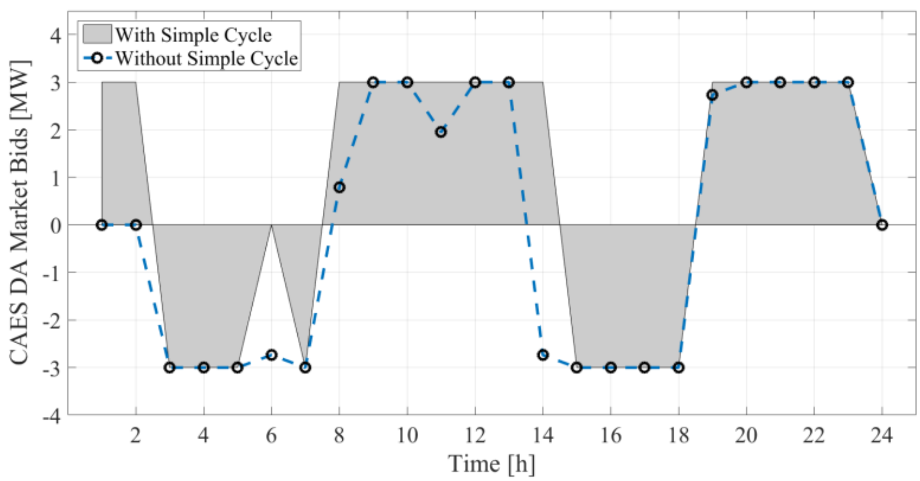


Fig. 3.17 Hourly power bids of CAES with/without CAES simple-cycle mode

3.7.4 Case IV: Considering CAES Simple-cycle Mode

This section investigates the coordination of CAES aggregator and WPA for participating in markets while considering the CAES simple-cycle mode, financial risk, and bidding curves. As similar to Case III, Eqs. (3.75), (3.60) and (3.86) are incorporated in the problem formulation of markets. Besides, $\zeta = 0.6$ is assigned to the risk factor. Simple-cycle mode of CAES is also added to the formulation.

Fig. 3.17 compares the hourly power bids of CAES (with/without simple-cycle mode) to the DA market when it works as a producer in the joint operation. It can be seen that CAES buys power from the market for fewer hours in the case of the simple-cycle mode. There is no need for CAES to charge the reservoir when the simple-cycle mode is considered. Furthermore, the CAES can offer power to the market for the first two hours of scheduling by utilizing the simple-cycle mode even though the cavern is at its initial minimum level (i.e., the cavern is empty at the starting point of scheduling). Simple-cycle mode can also assist the system operator in exploiting price strikes in the electricity market fully. The HPP has the opportunity to employ the CAES simple-cycle mode for an immediate power provision to the energy markets to attain the maximum profit of energy price fluctuations. As an illustration, this option is available when the energy price is high for a specific period, and no power can be provided by WPA (e.g., lack of wind) and CAES (e.g., there is no stored energy in the cavern).

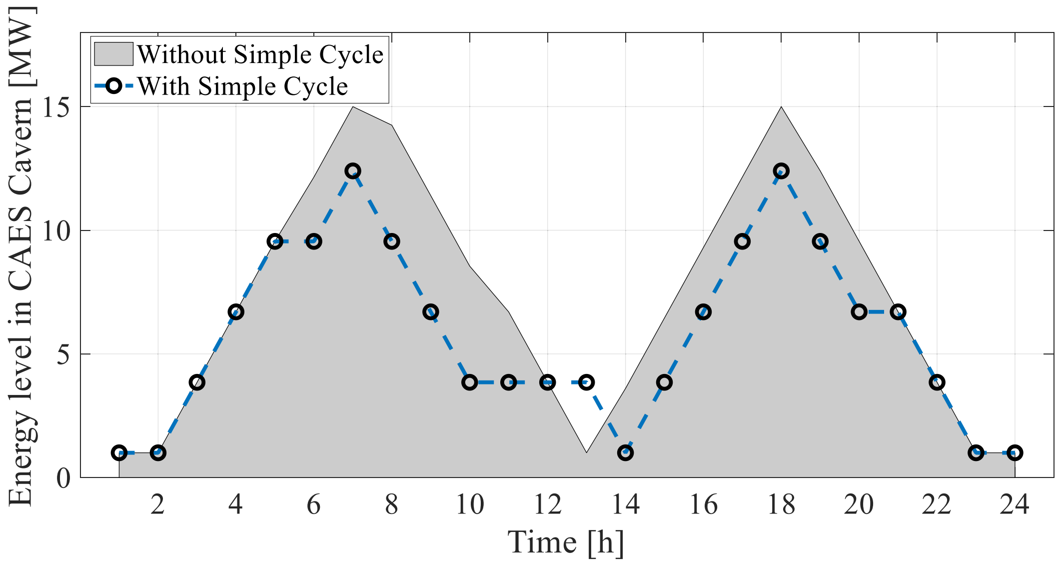


Fig. 3.18 Comparison of energy level changes in the CAES cavern with/without CAES simple-cycle mode.

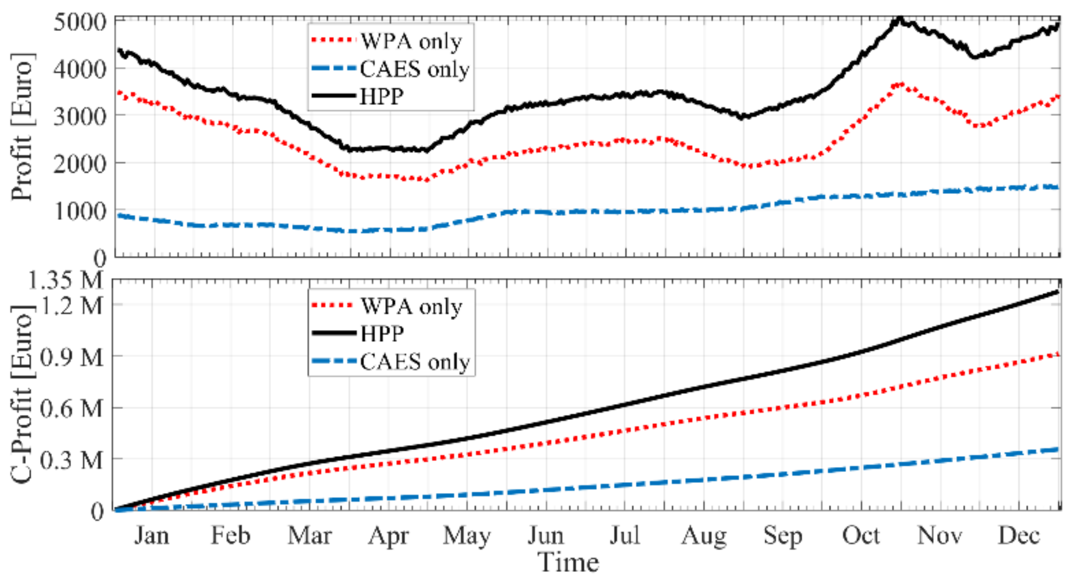


Fig. 3.19 Profit and cumulative profit (C-Profit) comparison for CAES only, WPA only and HPP over one year.

Fig. 3.18 compares changes of energy level in the cavern of CAES when it operates with/without the simple-cycle mode in the joint configuration. It is shown that the energy level of the cavern does not reach its maximum when using simple-cycle mode, which means it is financially more beneficial to sell power in this mode (e.g., hour 6). Also, some shifts can be observed in cavern depletion for some hours (e.g., 13 and 14) using the simple-cycle mode that indicates more flexibility of the proposed approach.

3.7.5 Case V: a case study over one year

This subsection investigates the HPP for participating in markets while considering the CAES simple-cycle mode, financial risk, and bidding curves for one year. Scenarios for wind power and electricity prices are generated based on the historical data of wind speed and market prices in the Iberian Peninsula electricity market for the year 2016. Fig. 3.19 shows the profit and cumulative profit (C-Profit) comparison for CAES only, WPA only and HPP over one year. As can be seen in Fig. 3.19, the daily profit of HPP is higher than the individual operation of WPA and CAES aggregators. Moreover, the cumulative profit of joint configuration is superior to the ones with independent configurations.

3.8 Summary

This chapter has proposed a methodology in the form of a three-stage problem for joint operation of a CAES aggregator and a WPA which participate in DA, intraday and balancing markets. This stochastic mixed-integer linear programming has been solved with an available commercial solver of GAMS software.

Firstly, a two-stage stochastic decision-making model for the participation of CAES aggregator has been modeled. Also, a simple-cycle mode has been added into the CAES operation to reach a more flexible operation for presented joint configuration in case of an electricity price strike. Secondly, a three-stage stochastic decision-making model is modeled for the participation of WPA. Then, a coordinated strategy of an HPP which includes a WPA and a CAES aggregator is modeled. The coordinated strategy of the HPP has been formulated as a three-stage stochastic optimization problem. To adjust the operation of the HPP to the mentioned markets, both bidding curves and bidding quantity have been modeled. A mixed-integer linear programming formulation has been obtained for the problem which can be easily solved by commercially available software such as GAMS. Also, in order to control the financial risks, the CVaR model has been added to the optimization problem. By using the join operation, the HPP has achieved more profit even when the financial risks are considered.

4 Risk-Constrained Demand Response and Wind Energy Systems Integration to Handle Stochastic Nature and Wind Power Outage

4.1 Motivation

Recent changes that have happened in the electricity networks increase the potential volume of DR that can be provided from industrial, commercial, or residential customers. For example, various studies consider the aggregation of DR resources [149-151], provision of DR from thermostatically controlled loads [152, 153] and electric vehicles [154, 155] for ancillary service provision [156], benefiting renewable energy resources [157, 158] and making HPPs [81]. In this regard, different publications have appeared in recent years which propose the utilization of DR resources to cope with the volatile characteristics of wind-based generation [81, 82]. Ref. [84] determines the optimum value of the DR unit to enhance the control of congestion as well as the use of wind-based generation. An offering policy for the combination of a flexible load and a WPA with the capability of covering the wind power imbalances is proposed in [85]. This join operation is formulated to participate in a DA electricity market. Total operating costs of a join aggregator comprising fines corresponding to wind energy over/under-commitment are minimized in [86] by proposing optimal scheduling based on critical peak pricing. This study is accomplished by utilizing a DR unit which employs wind power to suitably trade in the DA market. Ref. [87] presents an original offering plan for a WPA to participate in balancing, intraday, and DA electricity markets with the assist of a DR resource that is permitted to participate in the intraday market. Furthermore, a new technique is developed in [88] that models the uncertainties of the load and wind power for a corrective control of voltage to manage the challenging situations in which the power system experiences voltage instability as the result of severe contingencies.

4.2 Contributions and Approach

This chapter offers a methodology for the joint operation of a WPA and a DR aggregator (DRA) as an HPP in which the WPA utilizes the DRA as a storage unit. This HPP then offers the bids to the DA, intraday, and balancing markets. The uncertainties associated with wind power generation, its outages, and the price of energy in three markets are modeled through a set of scenarios, which results in a stochastic programming problem. The elasticity concept models the relationship between the electricity price and load consumption, and a probability distribution function models the outage times of wind generator. CVaR which is a well-known risk measure in the power market literature is also added to the final problem to control the cost deviations and financial risk.

4.3 Proposed Methodology

The structure of such an operation is presented in Fig. 4.1 which demonstrates individual offerings of wind generator owners and DR aggregators to the markets and also, the HPP offerings on behalf of both of them. This is achieved by formulating the problem as a stochastic programming problem which rightly considers the effects of bidding in the three electricity markets. The concern here is to compare the individual operation of DRAs and wind generators with their joint operation. In this regard, the comparisons are made from the perspective of the optimal offerings to the markets, the profits they earn and the risk considerations.

The offering outline of HPP is explained in this section. Three energy markets are considered in the market settlements which run in different time frames. For the DA market, the suppliers (customers) offer their bids to the market one day ahead of the actual delivery. Therefore, the closure of this market happens many hours before the real-time operation. On the other hand, the intraday market provides this opportunity for market participants to correct their offers that they previously made in the case that they cannot meet the pledged power supplies (demands). Finally, the balancing market runs near the real-time operation to cover the imbalances that may happen in the system. The intraday and balancing markets are suitable setups for WPAs to modify the offered bids as they cannot precisely predict the amount of produced power.

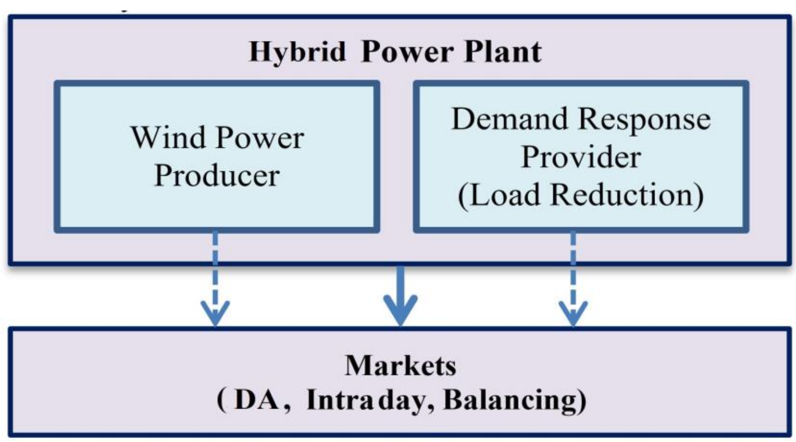


Fig. 4.1 Structure of Hybrid power plant

The presented model of HPP including the above three electricity markets is formulated as a profit (revenue of HPP minus its total cost) maximization problem. Then, the objective function $\mathcal{Z}_{Obj}^{HPP}$ of the underlying optimization problem, $\text{Max}_{\Theta c_{t,s};\varphi_s,\forall s;\theta}\left[\mathcal{Z}_{Obj}^{HPP}\right]$, can be formulated as (4.1).

$$\left[\mathcal{Z}_{Obj}^{HPP}\right] = \sum_{t=1}^{N_T}\sum_{s=1}^{N_S}\pi_s\left[\rho_{t,s}^{DA}.Ph_{t,s}^{DA} + \rho_{t,s}^{IN}.Ph_{t,s}^{IN} + \frac{1}{2}.\frac{1}{\Upsilon.d_{0t}}.\left(D_{t,s}^{SC}\right)^2 + \rho_{t,s}^{DA}.\eta_{t,s}^{+}.\varepsilon h_{t,s}^{+} - \rho_{t,s}^{DA}.\eta_{t,s}^{-}.\varepsilon h_{t,s}^{-}\right] + \zeta\left(\theta - \frac{1}{(1-\sigma)}\sum_{s=1}^{N_S}\pi_s\varphi_s\right). \tag{4.1}$$

The first part of this objective function shows the offering strategies of HPP in the three markets. The revenues are composed of two parts: wind power generation offerings in the markets and DR revenue which is achieved through load shifting. Based on the scenarios, the HPP could incur some costs from the balancing market, which are shown as a negative term in the objective function (4.1). The terms $\rho_{t,s}^{DA}.P_{t,s}^{DA}$ and $\rho_{t,s}^{IN}.Ph_{t,s}^{IN}$ are the revenue from DA market and revenue (cost) from the intraday market, respectively; while the terms $\rho_{t,s}^{DA}.\eta_{t,s}^{+}.\varepsilon h_{t,s}^{+}$ and $\rho_{t,s}^{DA}.\eta_{t,s}^{-}.\varepsilon h_{t,s}^{-}$ indicate the revenue/cost from the positive/negative energy deviations in the balancing market. Υ is a factor that defines the relationship between elasticity and price. d_{0t} is the normal level of demand in period t. $D_{t,s}^{SC}$ is the scheduled power of the demand side. The load model is derived based on the elasticity concept which illustrates the exponential relationship between the price ρ_t and demand D_t [81]:

$$D_t = k.e^{\varrho\cdot\rho_t} \tag{4.2}$$

where ϱ is a negative number and k is a constant. Similar to the last chapter, the last term in (4.1) is related to the modeling of CVaR measure. It is noteworthy that, as shown in Fig. 3.5,

$(1-\sigma)$ regulates the area of profit distribution function covering the least profitable scenarios.

Operating and aggregators' constraints associated with modeling of DRA, WPA are detailed in the following. The offer limitation of the HPP to the DA market can be written as follows:

$$0 \leq Ph_{t,s}^{DA} \leq Pw^{Max} + \phi_1 . d_{0t} \quad \forall t, \forall s \tag{4.3}$$

where $\phi_1 . d_{0t}$ is the capacity of DRA in which ϕ_1 is a factor that limits the usage range of the load in DRA. The minimum value for constraint (4.3) is zero because HPP is regarded as a generation company in this study. Eq. (4.4) formulates the scheduling power of HPP, including DA and intraday offers:

$$Ph_{t,s}^{SC} = Ph_{t,s}^{DA} + Ph_{t,s}^{IN} \quad \forall t, \forall s \tag{4.4}$$

The scheduled power of HPP is limited by (4.5):

$$0 \leq Ph_{t,s}^{SC} \leq Pw^{Max} + \phi_1 . d_{0t} \quad \forall t, \forall s \tag{4.5}$$

The HPP imbalances (i.e., total, negative, and positive) based on the power production of WPA and DRA can be written as follows:

$$\varepsilon h_{t,s} = Pw_{t,s} + D_{t,s} - Ph_{t,s}^{SC} \quad \forall t, \forall s \tag{4.6}$$

$$\varepsilon h_{t,s} = \varepsilon h_{t,s}^{+} - \varepsilon h_{t,s}^{-} \quad \forall t, \forall s \tag{4.7}$$

$$0 \leq \varepsilon h_{t,s}^{+} \leq Pw_{t,s} + D_{t,s} \quad \forall t, \forall s \tag{4.8}$$

$$0 \leq \varepsilon h_{t,s}^{-} \leq Pw^{Max} + \phi_1 . d_{0t} \quad \forall t, \forall s \tag{4.9}$$

where $Pw_{t,s}$ and $D_{t,s}$ are delivered power production of WPA and DRA, respectively. It is an assumption in this chapter that the scheduled value of DRA and its active power are equal, which means no uncertainty has been considered for DRA production. The limit of intraday offer can be expressed as follows:

$$-\Lambda . Ph_{t,s}^{DA} \leq Ph_{t,s}^{IN} \leq \Lambda . Ph_{t,s}^{DA} \quad \forall t, \forall s. \tag{4.10}$$

The following constraints are employed to calculate the risk factor:

$$-\sum_{t=1}^{N_T} \left[\rho_{t,s}^{DA} . Ph_{t,s}^{DA} + \rho_{t,s}^{IN} . Ph_{t,s}^{IN} + \frac{1}{2} . \frac{1}{\Upsilon . d_{0t}} . \left(D_{t,s}^{SC} \right)^2 + \rho_{t,s}^{DA} . \eta_{t,s}^{+} . \varepsilon h_{t,s}^{+} - \rho_{t,s}^{DA} . \eta_{t,s}^{-} . \varepsilon h_{t,s}^{-} \right]$$

$$+ \ \theta - \varphi_s \leq 0 \quad \forall s \tag{4.11}$$

$$\varphi_s \geq 0 \quad \forall s. \tag{4.12}$$

The constraints related to the modeling of flexible load are mathematically expressed by (4.13)-(4.18):

$$D_{t,s}^{SC} = D_t^{DA} + D_{t,s}^{IN} \quad \forall t, \forall s \tag{4.13}$$

$$\phi_2 . d_{0t} \leq D_t^{DA} \leq \phi_1 . d_{0t} \quad \forall t, \forall s \tag{4.14}$$

$$\phi_2 . d_{0t} \leq D_{t,s}^{SC} \leq \phi_1 . d_{0t} \quad \forall t, \forall s \tag{4.15}$$

$$\sum_{t=1}^{N_T} D_{t,s}^{SC} \leq \mu . \sum_{t=1}^{N_T} d_{0t} \quad \forall s \tag{4.16}$$

$$D_{t,s}^{SC} = D_{t,s'}^{SC} \quad \forall t, \forall s, \forall s' \quad if \quad \rho_{t,s}^{DA} = \rho_{t,s'}^{DA} \tag{4.17}$$

$$D_{t,s}^{IN} = D_{t,s'}^{IN} \quad \forall t, \forall s, \forall s' \quad if \quad \rho_{t,s}^{DA} = \rho_{t,s'}^{DA} \tag{4.18}$$

Eqs. (4.17) and (4.18) define the non-anticipativity of decisions in the market of intraday. The lower bounds of constraints (4.14)-(4.15) are changed from zero to $\phi_2 . d_{0t}$ ($\phi_2 < 0$) because the DRA can exploit wind power units and escalate its load in the joint operation. Eq. (4.16) models the flexibility of load where μ is a factor that limits the maximum range of the total loads in N_T hours. In order to propose non-decreasing curves of offering to the DA market, two constraints are defined as follows:

$$\left(Ph_{t,s}^{DA} - Ph_{t,s'}^{DA}\right).\left(\rho_{t,s}^{DA} - \rho_{t,s'}^{DA}\right) \geq 0 \quad \forall t, \forall s, \forall s' \tag{4.19}$$

$$Ph_{t,s}^{DA} = Ph_{t,s'}^{DA} \quad \forall t, \forall s, \forall s' \quad if \quad \rho_{t,s}^{DA} = \rho_{t,s'}^{DA} \tag{4.20}$$

4.4 Case Study and Results

4.4.1 Assumptions and data

The proposed approach aims to coordinate a WPA and a DRA while tackling the uncertainties associated with the production of WPA, electricity prices in electricity markets, and outage of wind power. To this end, three different structures as depicted in Fig. 4.1 is simulated including DRA only, WPA only, and HPP. Uncertainties of markets' price and wind power are generated and modeled with some scenarios utilizing a joint block of a hybrid Jaya algorithm and an adapted virtual neural network. Statistical analysis is used to generate scenarios regarding severe outages of the wind units.

The proposed technique is applied on a real wind farm in the Sotavento of Spain with a capacity of 17.56 MW [99]. The chaotic feature of wind power is generated by the procedure proposed in [81]. Historical data of the year 2010 is utilized for training the artificial neural network. Based on the procedure presented in [144], a three-step formulation is employed in this study for modeling market prices. The historical data of market prices and demand are based on the electricity market of the Iberian Peninsula [159]. A scenario-tree based approach is applied for uncertainty modeling of the problem which contains 3000 scenarios (6×10×5×10) with six, ten, five and, ten scenarios for wind generation, and prices in DA, intraday and balancing markets, respectively. Fig. 3.6 shows the flowchart of the stochastic modeling process. Randomly generated values are used for outage times of the wind power. Table 4.1 details the probability distribution for the outage times of wind power.

The outage times shown in this table are added to the previously generated stochastic profile of wind generation. The data for March 12, 2010, is used for obtaining simulation results. It is assumed that 0.067% of the total electricity loads of the Spanish grid are united to take part as a DRA in the market.

The scenario generation/reduction procedure of the proposed method is primarily executed in MATLAB software and then the results are imported into the GAMS software through a GAMS/MATLAB interface to solve the given optimization problem. Note that CPLEX is used as the solver of the GAMS software. The execution time of simulations is 120.756 seconds on a 2.3 GHz Intel® CORE^{TM} i5 laptop with 8 GB of RAM.

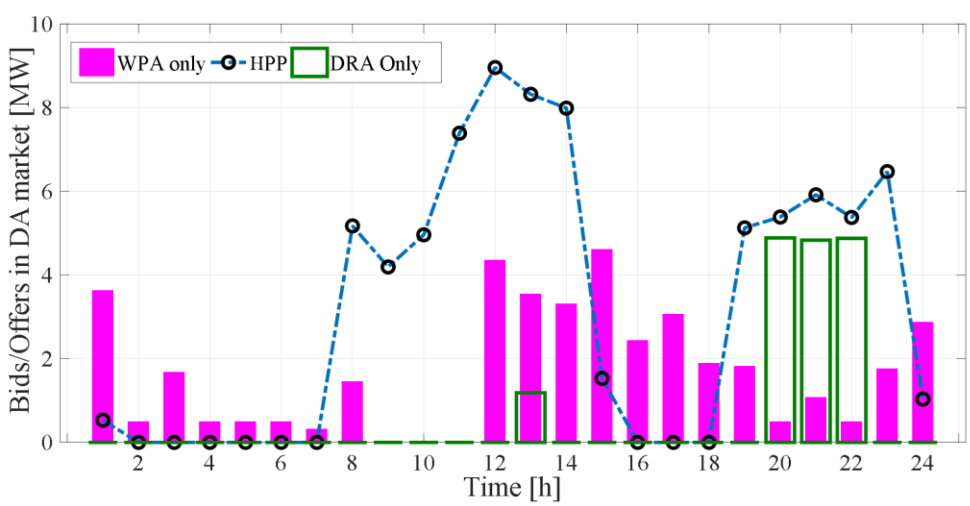


Fig. 4.2 Optimal hourly power bids for the DA market

Table 4.1 Distribution of outage time probability for WPA

Parameters	**Probability Distribution Characteristics**			
	St. Dev.	**Mean**	**Max.**	**Min.**
T^{Start}	1	13.5	16	11
T^{Stop}	1	20	23	17

4.4.2 Numerical Studies

In this chapter, four studies are done to evaluate the applicability and effectiveness of the proposed approach as follows:

1) Comparison of power bids

In this section, the effect of the joint operation of DR and wind producers on their power offerings will be discussed. Hourly power bids to the DA market for scenario #5 are depicted in Fig. 4.2 regarding different configurations: WPA only, HPP operation, and DRA only, while the generation system experiences a wind outage condition. As can be seen, DRA with the assist of WPA can store more energy in the joint operation during the hours of off-peak, while this stored energy is released to the market during the peak hours. Moreover, the strategy for joint operation obtains €96.171 extra profits compared to two other independent operation strategies.

Fig. 4.3 shows the optimal variations in the behavior of demand response provider for each scenario in the joint operation for the DA market. It can be seen from this figure that the DR provider has different responses corresponding to different DA market scenarios.

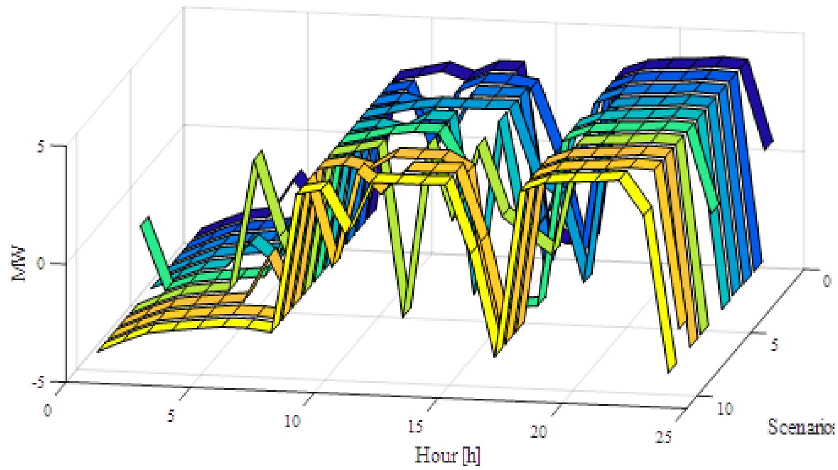


Fig. 4.3 Optimal variations in the behavior of demand response provider for each scenario in the joint operation.

Optimal power bids of independent HPP and WPA are shown in Fig. 4.4 and Fig. 4.5 for scenario #5 under two conditions of normal operation and wind outage. Obviously, independent WPA provides no offer during the periods of wind power outage including hours 9-12 and hours 14-23.

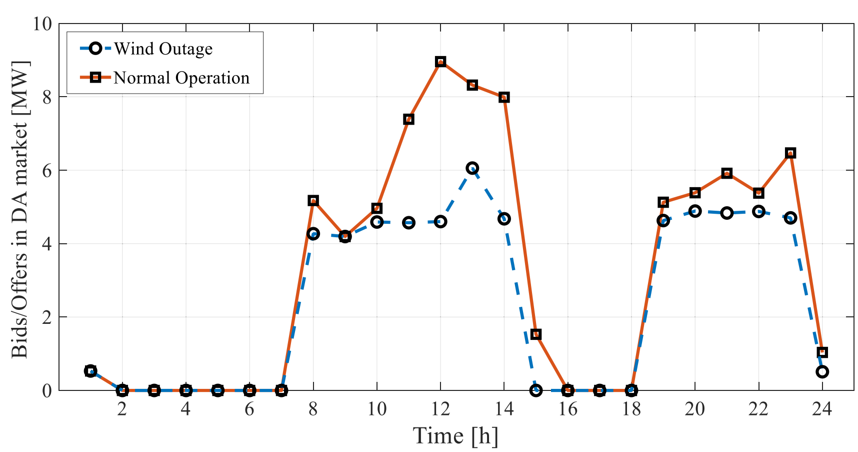


Fig. 4.4 HPP optimal power bids in the DA market under normal operation and wind outage

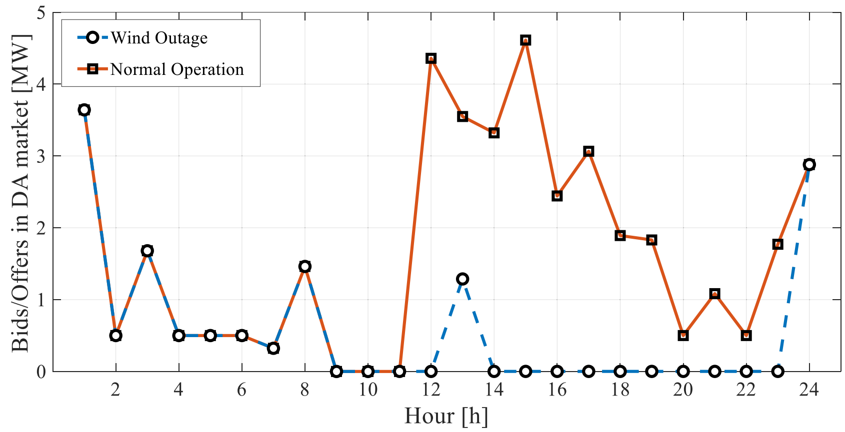


Fig. 4.5 Optimal power bids of independent WPA in the DA market under normal operation and wind outage.

However, the HPP offers slightly less power to the DA market when the occurrence of the wind outage compared to the normal condition. The optimal bids of DRA in the DA market under both conditions of independent and joint operation are shown in Fig. 4.6. As can be illustrated, near the full capacity of the DRA can be utilized in some hours when it cooperates with the WPA.

2) Comparison of profits

Fig. 4.7 shows the hourly comparison of the expected net profit for three given configurations while considering wind outage. Based on this figure, especially around 7 a.m. till 3 p.m., the hourly profits are increased significantly. However, for about three hours (3 p.m. till 6 p.m.), HPP incurs some losses due to the offering policies that it takes for maximizing the profit. On the other hand, the behavior of HPP and DRA during peak hours is quite interesting. As anticipated, the DR offers most of the load shifting in this period as usually, the highest electricity price happens in this time frame, and the highest profit can be earned. Consequently, HPP also earns great profit in this period as it possesses the DR.

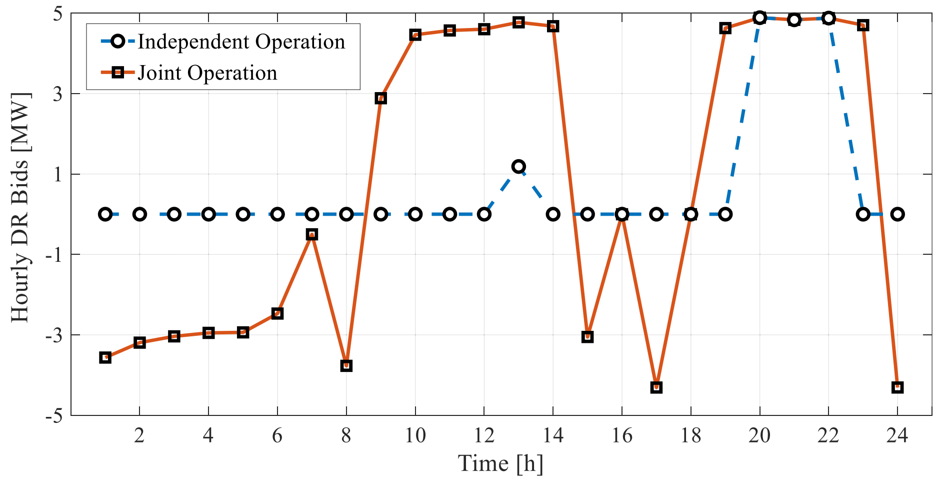


Fig. 4.6 Optimal power bids of DRA in the DA market under independent operation and joint operation.

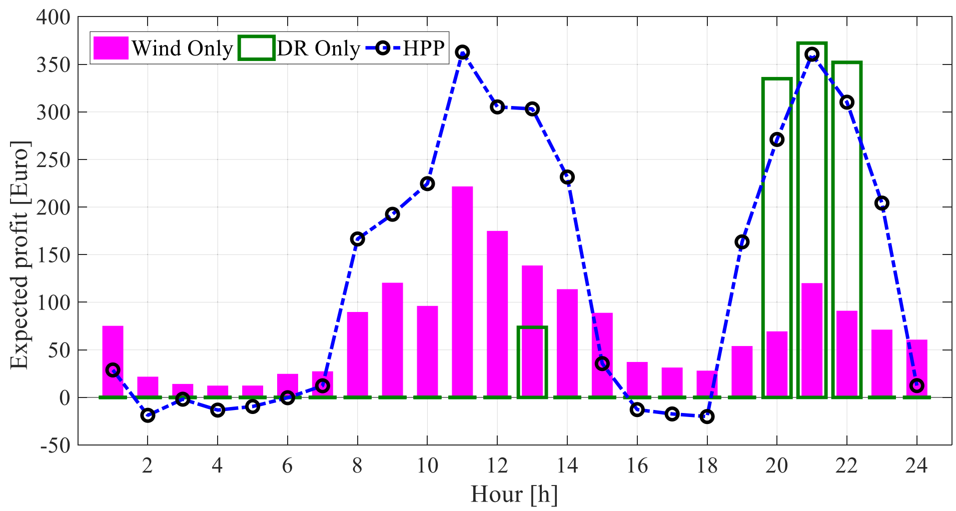


Fig. 4.7 Hourly comparison of expected net profit under three configurations: DRA only, WPA only, and HPP

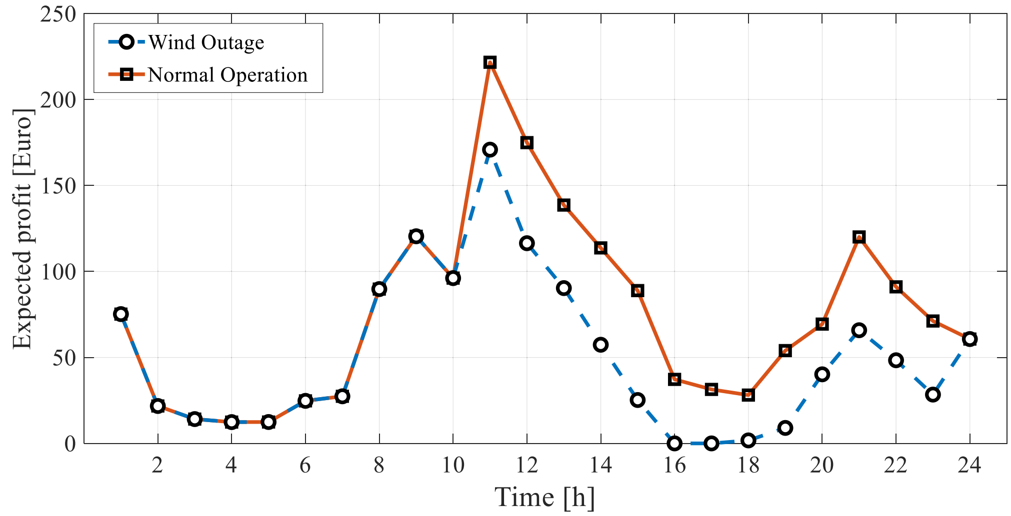


Fig. 4.8 Hourly expected net profit of independent WPA under two different conditions of normal operation and wind outage.

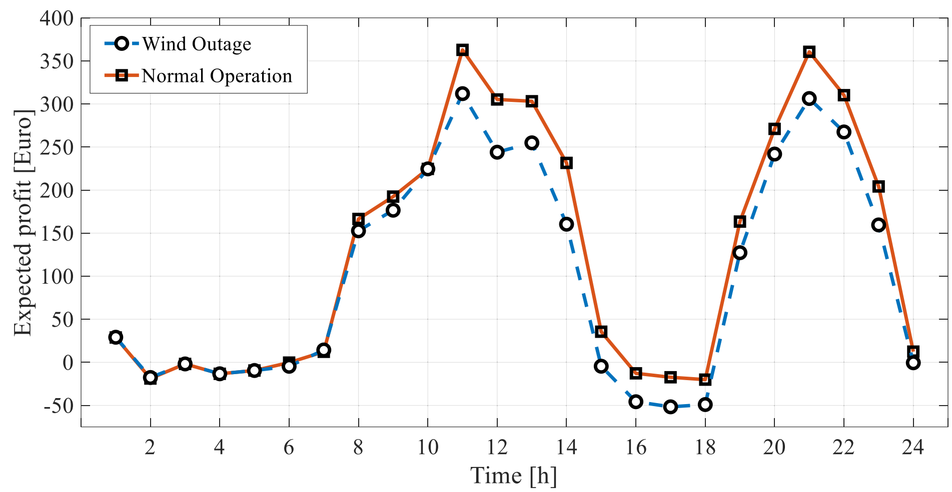


Fig. 4.9 Expected net profit of HPP under two different conditions of normal operation and wind outage.

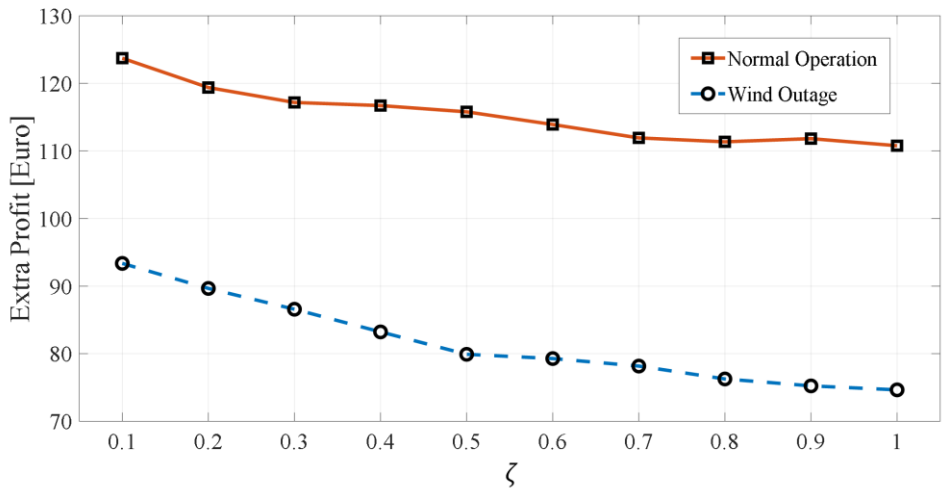


Fig. 4.10 Extra profit comparison of HPP for a set of ζ values under two conditions of wind outage and normal operation.

Furthermore, Fig. 4.8 and Fig. 4.9 show the hourly expected profit of the independent WPA and HPP under two conditions of normal operation and wind outage. Comparison of these figures also demonstrates the benefits of joint operation as the wind outage has less effect on the expected profits of HPP than the individual utilization of wind generator. Note that this expected profit of wind producer in the outage period is not zero in all outage hours (see Table 4.1), because the expected profit is based on all probable scenarios.

3) Effect of the risk

As mentioned earlier, risk consideration is a crucial matter that affects the final decision of all participants in electricity markets. Maximization of the expected value of profit does not necessarily mean that scenarios with low profits or even negative ones will not occur. Those scenarios can have a non-negligible probability of occurrence. To limit the effect of those undesired scenarios, a risk measure is usually added to the final formulation. In the CVaR risk measure, the weight of the risk on the final problem is determined by the risk factor ζ.

Fig. 4.10 shows the extra profits of HPP under two conditions of wind outage and normal operation for different values of the risk factor ζ. As illustrated from this figure, the extra profits of HPP are declined with the increasing ζ.

It should be mentioned that an increase in risk factor ζ causes the extra profit to be decreased under both normal operation and wind outage conditions. As can be seen, the maximum extra profit (i.e., 124.056 Euros) is attained under the normal condition at the risk factor $\zeta = 0.1$, while its minimum value (i.e. 74.986 Euros) is reached at $\zeta = 1$ under the condition of wind outage.

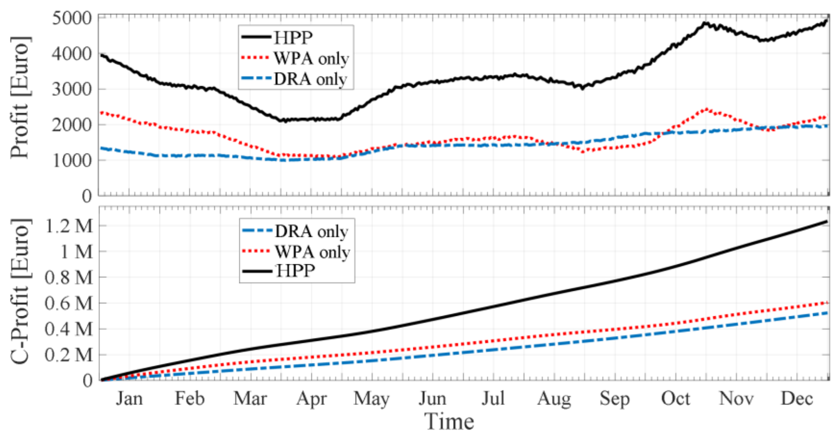


Fig. 4.11 Profit and cumulative profit (C-Profit) comparison for DRA only, WPA only and HPP for one year

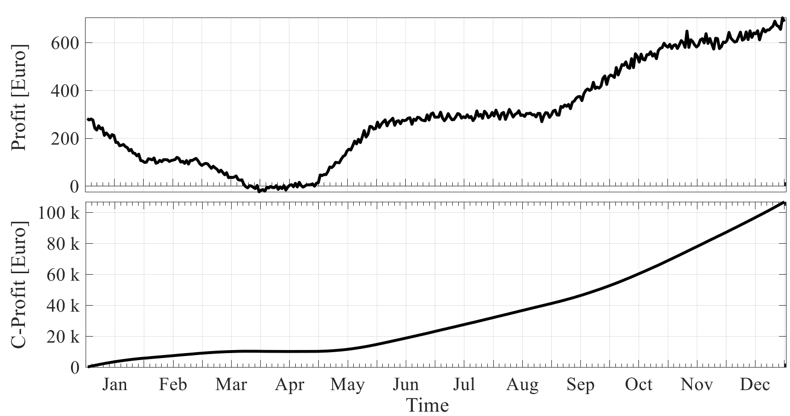


Fig. 4.12 Profit and cumulative profit (C-Profit) for an extra profit of HPP over one year

4) Case study over one year

This case study analyses the HPP for contributing to the three markets over one year. Scenarios for wind power and electricity prices are produced based on the historical data of wind speed and the Iberian Peninsula electricity market for the year 2016. Fig. 4.11 compares the profit and cumulative profit (C-Profit) for the three configurations including DRA only, WPA only and HPP for one year. As can be seen in Fig. 4.11, the daily profit of HPP is higher than the individual operation of WPA and DRA. Moreover, the cumulative profit of HPP is superior to the ones with independent configurations.

Fig. 4.12 also investigates the profit and C-Profit for the extra profit of HPP over one year. As seen, the maximum amount of extra profit happens at the end of the year when the price of electricity is too high. The total amount of extra profit of HPP for this year is 106850 Euros.

4.5 Summary

This chapter coordinates a WPA and a DRA to form an HPP which participates in different types of electricity markets comprising DA, intraday, and balancing markets. The price of energy in electricity markets, wind production, and its outage are considered as uncertain parameters.

Firstly, a two-stage stochastic programming model has been formulated for a DRA. The relationship between the electricity price and load consumption is modeled by the elasticity concept. Then, using the WPA model obtained in Section 3.3 and DRA model of this chapter, a joint operation of a WPA and a DRA is formulated as an HPP in which the WPA utilizes the DRA as a storage unit. Also, a random procedure has been utilized to generate the uncertainty of wind outage which is added to the normal operation of wind producer.

Three-stage stochastic programming has been formulated to clear the DA market in this first stage, while the intraday market and balancing market are cleared afterward in the next two stages. The uncertainties associated with wind power generation, its outages, and the price energy in three markets have been modeled through a set of scenarios. CVaR technique has been applied to the formulation of problems to tackle the financial risk of the market operation. The results demonstrated the superiorities of joint operation as an HPP compared to the independent participation of wind and DR producers in the markets.

5 Hybrid Power Plant Bidding Strategy for Voltage Stability Improvement, Electricity Market Profit Maximization, and Congestion Management

5.1 Motivation and Contributions

Due to the stochastic, unstable, and nondispatchable nature of wind generations, it is usually very difficult for these kinds of producers to participate in electricity markets and compete with other producers such as conventional power plants. For this reason, it is important to offer a new strategy for WPAs to help them overcome these difficulties.

The network constraints can also affect the scheduling of the generators and storage units like WPA and CAES. Depending on the objective function that the decision-maker aims to optimize, the power scheduling of the mentioned aggregators can be different. For example, if the objective function is to optimize the electricity market profit, the aggregators would follow the price of electricity markets, but if the objective function is to minimize the congestion management, the scheduling would be different to change the power flow through the network.

A few studies provide offering strategies for different types of aggregators, considering network constraints. For example, Ref. [88] presents a novel method considering the uncertainty related to the amount of wind power generation and load for corrective voltage control to cope with the states in which the power systems experience voltage instability due to severe contingencies. A probabilistic optimal power flow approach is formulated in [160] for an HPP that is comprised of plug-in electric vehicles, photovoltaic and wind energy sources. In that study, the Monte Carlo simulation is used to generate the PDF of the stochastic powers. A new fuzzy algorithm is used to solve the security-constrained optimal power flow problem in [161] with wind and thermal power generators, where wind power uncertainties are modeled using Weibull probability function.

In this chapter, a CAES aggregator equipped with a simple cycle mode operation having the ability to work as a gas turbine is coordinated with a WPA as an HPP to participate in the DA electricity market considering network constraints. In the proposed approach, the WPA uses the CAES to tackle its stochastic input and uncertainties related to different electricity market prices, and CAES can also use WPA to manage its charging/discharging and simple cycle modes more economically. Three objective functions are considered including electricity market maximization, congestion management, and voltage stability improvement. The problem is formulated as a multi-objective mixed integer nonlinear programming problem which is solved using an artificial algorithm. Multi-objective Pareto front solutions are used to optimize all three objective functions simultaneously. The best compromise solution is also suggested using the fuzzy method. The proposed method is tested on a realistic case study based on a wind farm and electricity market located in Spain, and IEEE 57-bus test system is used to analyze the network constraints effects. The contributions of the chapter are briefly specified as follows:

- An HPP including a CAES aggregator and a WPA is modeled considering network constraints.

- Three objective functions are considered, including electricity market maximization, congestion management, and voltage stability improvement.
- In order to properly model the WPA, pitch control for wind power curtailment is added to wind generator modeling.
- The proposed approach is tested on a real case study based on a wind farm and electricity market located in Spain, and the IEEE 57-bus test system is used to analyze the effects of network constraint on the HPP scheduling for different objective functions.

5.2 Problem Formulation

Three objective functions are considered in this chapter, including profit maximization, voltage stability, and congestion management. The first objective function is profit maximization, which is equal to the revenue of the HPP minus its total cost.

$$\mathrm{Max}_{\Theta h_{t,s}}[\mathcal{Z}_1]$$

$$\mathcal{Z}_1 = \sum_{s=1}^{N_s}\sum_{t=1}^{N_T}\pi_s\left[\rho_{t,s}^{DA}.Ph_{t,s}^{DA} - OC_{t,s}\right] \tag{5.1}$$

where $\Theta h_{t,s} = \{Ph_{t,s}^{DA}, Uw_{t,s}^{DA}, Pw_{t,s}^{DA}, Pc_{t,s}^{DA}, Pc_{t,s}^{DA,Dis}, Pc_{t,s}^{DA,Sim}, Pc_{t,s}^{DA,Cha}, Uc_{t,s}^{DA,Dis}, \beth_t$ $Uc_{t,s}^{DA,Sim}, Uc_{t,s}^{DA,Cha}, Ec_{t,s}^{DA}\ \}, \forall t,\ \forall s$ are the variables related to the HPP optimization problem. s is an index of scenario and N_{Ω} is the total number of scenarios. t and N_T are the index of the time period and the total number of periods, respectively. π_s is the probability of occurrence of each scenario. $\rho_{t,s}^{DA}$ is the DA market price. $Ph_{t,s}^{DA}$ is DA offer of the HPP.

$OC_{t,s}$ is the operational cost of CAES, which is calculated based on the amount of power in charging/discharging and simple cycle modes; see (5.16).

The objective function defined in (5.1) is subject to some combined constraints related to the WPA, commercial CAES provider, and the conventional power plants aggregators, and some other constraints specifically related to each of them.

The offer limitation of the HPP in the DA market can be written as follows:

$$Ph_{t,s}^{DA} = Pw_{t,s}^{DA} + Pc_{t,s}^{DA} \quad \forall t, \forall s \tag{5.2}$$

where $Pw_{t,s}^{DA}$ and $Pc_{t,s}^{DA}$ are the amount of wind and CAES powers offered to the DA market limited to the following constraints:

$$0 \leq Pw_{t,s}^{DA} \leq Pw^{Max} \quad \forall t, \forall s \tag{5.3}$$

$$-Pc_{Com}^{Max} \leq Pc_{t,s}^{DA} \leq Pc_{Exp}^{Max} \quad \forall t, \forall s \tag{5.4}$$

here Pw^{Max} is the WPA capacity. Pc_{Exp}^{Max} and Pc_{Com}^{Max} are the maximum expanding and compressing capacity of CAES, respectively. Note that $Pc_{t,s}^{DA}$ in (5.4) can get negative values, which means the HPP is considered to have the permission of both buying and selling in the DA market.

In order to properly model the WPA, the pitch angle control is added to wind generators using Eq. (5.5) to curtail the wind power level. Eq. (5.5) refers to how wind power PDF is modified after curtailment [162].

$$\bar{\pi}w_{t,h}^{DA} = \begin{cases} \pi w_{t,h}^{DA} & if \quad g_{t,h}^{DA} < g_{t,\beth_t}^{DA} \\ \sum\limits_{j \geq \beth_t} \pi w_{t,j}^{DA} & if \quad g_{t,h}^{DA} = g_{t,\beth_t}^{DA} \\ 0 & if \quad g_{t,h}^{DA} > g_{t,\beth_t}^{DA} \end{cases} \tag{5.5}$$

where $g_{t,h}^{DA}$ is the discrete realization of wind power, $g_{t,ב_t}^{DA}$ is the maximum hourly caps further than which all the wind power will be dropped, and h and $ב_t$ are wind power discrete levels and the wind curtailment decision variable, respectively. $ב_t$ values are between 1 and 7 in this chapter. $\bar{\pi}w_{t,h}^{DA}$ is the probability of wind power equal to $g_{t,h}^{DA}$ when the wind is curtailed. $\pi w_{t,h}^{DA}$ is the probability of wind power equal to $g_{t,h}^{DA}$.

In order to demonstrate the process, examples of two wind power PDFs are presented in Fig. 5.1. The wind power is distributed in 7 levels with their associated probabilities as shown in Fig. 5.1(a), while the wind power is curtailed on its 5th level as shown in Fig. 5.1(b), and the probabilities of level 6 and 7 are added to level 5.

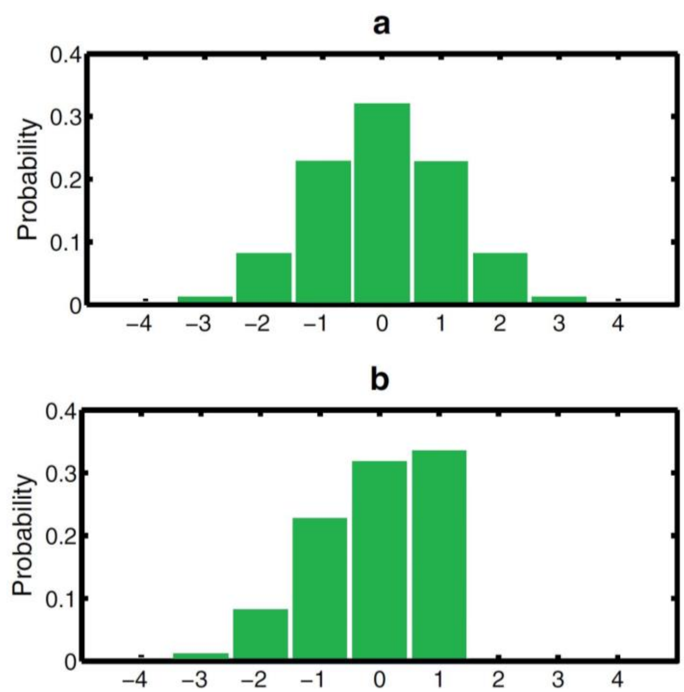


Fig. 5.1 (a) Initial wind power PDF; (b) the curtailed wind power PDF

Moreover, there are some constraints related to $Pc_{t,s}^{DA}$ as follows:

$$Pc_{t,s}^{DA} = Pc_{t,s}^{DA,Dis} + Pc_{t,s}^{DA,Sim} - Pc_{t,s}^{DA,Cha} \quad \forall t, \forall s \tag{5.6}$$

where $Pc_{t,s}^{DA,Dis}$, $Pc_{t,s}^{DA,Sim}$ and $Pc_{t,s}^{DA,Cha}$ are the amount of discharging, simple cycle and charging powers of CAES for the DA market. The limitations of CAES power in different modes of operation are as follows:

$$0 \leq Pc_{t,s}^{DA,Dis} \leq Pc_{Exp}^{Max}.Uc_{t,s}^{DA,Dis} \quad \forall t, \forall s \tag{5.7}$$

$$0 \leq Pc_{t,s}^{DA,Sim} \leq Pc_{Exp}^{Max}.Uc_{t,s}^{DA,Sim} \quad \forall t, \forall s \tag{5.8}$$

$$0 \leq Pc_{t,s}^{DA,Cha} \leq P_{Com}^{Max}.Uc_{t,s}^{DA,Cha} \quad \forall t, \forall \omega \tag{5.9}$$

where $Uc_{t,s}^{DA,Dis}$, $Uc_{t,s}^{DA,Sim}$ and $Uc_{t,s}^{DA,Cha}$ are the binary variables that show the operating status of the CAES (*i.e.* discharging, simple cycle or charging modes). Note that the CAES can only operate in one of the mentioned modes at each of the periods and scenarios. This concept can be mathematically formulated as the following constraint:

$$Uc_{t,s}^{DA,Dis} + Uc_{t,s}^{DA,Sim} + Uc_{t,s}^{DA,Cha} \leq 1 \;\; \forall t, \forall s \tag{5.10}$$

In this chapter, it is assumed that there is no uncertainty in the case of CAES power production.

The energy level of the CAES (*i.e.* also called state-transition equation) is defined as follows:

$$Ec_{t,s}^{DA} = Ec_{t-1,s}^{DA} + Er\left(Pc_{t,s}^{DA,Cha} - Pc_{t,s}^{DA,Dis}\right) \quad \forall t > 1, \forall s \tag{5.11}$$

$$Ec_{1,s}^{DA} = Ec^{INT} \quad \forall s \tag{5.12}$$

$$Ec^{Min} \leq Ec_{t,s}^{DA} \leq Ec^{Max} \quad \forall t, \forall s \tag{5.13}$$

where Er is the energy rate ratio that converts the value of power to the energy. Ec^{Min} and Ec^{Max} are the minimum and maximum amount of energy level that can be scheduled for the CAES, respectively.

In order to propose non-decreasing curves to the DA market and applying them to the unpredictable conditions related to the decisions made in this market, the following constraints can be defined:

$$\left(Ph_{t,s}^{DA} - Ph_{t,s'}^{DA}\right).\left(\rho_{t,s}^{DA} - \rho_{t,s'}^{DA}\right) \geq 0 \quad \forall t, \forall s, \forall s' \tag{5.14}$$

$$Ph_{t,s}^{DA} = Ph_{t,s'}^{DA} \quad \forall t, \forall s, \forall s' : \rho_{t,s}^{DA} = \rho_{t,s'}^{DA} \tag{5.15}$$

Finally, the equation related to the operational cost of CAES can be written as follows:

$$OC_{t,s} = Pc_{t,s}^{DA,Dis}\left(Hc^{Dis}.NG + Vc^{Exp}\right) + Pc_{t,s}^{DA,Sim}\left(Hc^{Sim}.NG + Vc^{Exp} + Vc^{Com}\right) + Pc_{t,s}^{DA,Cha}Vc^{Com} \quad \forall t, \forall s \tag{5.16}$$

where Hc^{Dis} and Hc^{Sim} are the heat rate in the discharging and simple cycle modes, respectively. Vc^{Exp} and Vc^{Com} are the variable operation and maintenance cost for the expander and compressor of the CAES. NG refers to the natural gas price.

The second objective function considered in this chapter is voltage stability improvement. The static voltage stability margin can be dignified through the minimal Ꝁ index as formulated in (5.17) [163, 164]:

$$\overline{Ꝁ}_j = \left|1 - \sum_{i \in \boldsymbol{B}_G} И_{ji}\frac{V_i}{V_j}\right| \quad j \in \boldsymbol{B}_L \tag{5.17}$$

where $\boldsymbol{B}_L$ and $\boldsymbol{B}_G$ are sets of load buses and generator buses, respectively. The matrix (И) in (5.17) can be calculated by (5.18):

$$[И] = -[Y_{LL}]^{-1}[Y_{LG}] \tag{5.18}$$

where $[Y_{LL}]$ and $[Y_{LG}]$ are the submatrices of the admittance matrix $Y_{bus} = \begin{bmatrix} Y_{LL} & Y_{LG} \\ Y_{GL} & Y_{GG} \end{bmatrix}$ partitioned in accordance with the load buses ($\boldsymbol{B}_L$) and generator buses ($\boldsymbol{B}_G$).

In stable conditions, $Ꝃ_j$ indices are required to be between 0 and 1. Therefore, an overall indicator $\overline{Ꝃ}$ that defines the stability of the whole system can be transcribed as the maximum of the $Ꝃ_j$ indices. The minimum of this overall indicator can be defined as an objective function as shown in (5.19):

$$\mathrm{Min}_{\Theta h_{t,s}}[\mathcal{Z}_2]$$

$$\mathcal{Z}_2 = \overline{Ꝃ} = \max(Ꝃ_j) \quad j \in \boldsymbol{B}_L \tag{5.19}$$

The third objective function considered in this chapter is congestion management. For the sake of simplicity, it is assumed that the maximum amount of power of each network line is the same. In order to consider congestion management in the problem, we try to minimize the maximum power through the lines of the network. Also, the penalty factor is implemented to eliminate the solutions which lead to over congestion through the network. The powers through the lines of the network can be written as in (5.20).

$$\boldsymbol{P}_{line} = [P_1 \quad P_2 \quad P_3 \quad \cdots \quad P_{N_{line}}], \tag{5.20}$$

where N_{line} is the total number of lines in the network. The penalty factor to reject the solutions which lead to over congestion through the network can be formulated using (5.21) and (5.22):

$$BP_l = \begin{cases} 0 & P_l \le P_l^{max} \\ 1 & P_l > P_l^{max} \end{cases} \quad , \forall l \epsilon [1, 2, \dots, N_{line}] \tag{5.21}$$

$$Penalty\ factor = m \times \sum_{l=1}^{N_{line}} BP_l \tag{5.22}$$

where P_l^{max} is the maximum volume of power that can be passed from end to end of the line l, and m is a large number (for instance, 10^{100}). As mentioned, the maximum amount of power of all lines is presumed to be equal. Therefore, the third objective function, which is to minimize the maximum power through the lines of the network, can be written as in (5.23). Note that if the maximum amount of power in lines is different, the normalized value of power passing through the line can be considered in the formulation.

$$\mathrm{Min}_{\Theta h_{t,s}}[\mathcal{Z}_3]$$

$$\mathcal{Z}_3 = \max(\boldsymbol{P}_{line}) + Penalty\ factor \tag{5.23}$$

5.2.1 Equality constraints

The optimal power flow equality constraints, including active and reactive powers, can be written as the following equations:

$$P_{gi} - P_{di} = \sum_{j=1}^{n_b} V_i V_j (G_{ij} cos\theta_{ij} + B_{ij} sin\theta_{ij}) \tag{5.24}$$

$$Q_{gi} - Q_{di} = \sum_{j=1}^{n_b} V_i V_j (G_{ij} sin\theta_{ij} - B_{ij} cos\theta_{ij}) \tag{5.25}$$

where G_{ij} and B_{ij} are the real and imaginary parts of the network admittance matrix element Y_{ij}, respectively, so that $Y_{ij} = G_{ij} + jB_{ij}$. P_{gi} and P_{di} are the real power generation and consumption of the i^{th} bus. Q_{gi} and Q_{di} are the reactive power generation and consumption of the i^{th} bus. θ_{ij} is the voltage angle difference between bus i and bus j.

5.2.2 Inequality constraints:

The optimal power flow inequality constraints include active and reactive power generation of each generator (Eqs. (5.26) and (5.27)), the active power passing through the lines (Eq. (5.28)), and the voltage profile of each load bus (Eq. (5.29)).

$$P_{gi\,min} \leq P_{gi} \leq P_{gi\,max} \qquad i \in \boldsymbol{B}_G \tag{5.26}$$

$$Q_{gi\,min} \leq Q_{gi} \leq Q_{gi\,max} \qquad i \in \boldsymbol{B}_G \tag{5.27}$$

$$\left|P_{ij}\right| \leq P_{ij\,max} \tag{5.28}$$

$$V_{i\,min} \leq V_i \leq V_{i\,max} \qquad i \in \boldsymbol{B}_L \tag{5.29}$$

where the subscript *max* and *min* indicate, respectively, the maximum and minimum values. Note that Matpower M-file package is used to solve the optimal power flow. Equality and inequality constraints are completely satisfied in the process of solving optimal power flow with Matpower.

5.2.3 Multi-objective Strategy and Optimization Tool

In this section, the multi-objective technique and its concept are introduced. Fig. 5.2 shows the concept of multi-objective Pareto solutions for two objective functions. As shown in Fig. 5.2, all populations are arranged with the best values of the objective functions, and the dominated solutions are identified and removed.

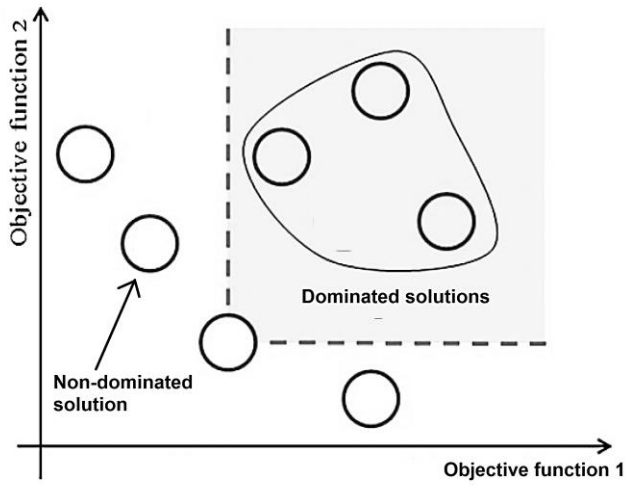


Fig. 5.2 Pareto-optimal front concept for two objective functions

The values of the objective functions are usually quite different. For example, in this study, the profit maximization objective function values are about 1 million, and voltage stability objective function values are between 0 and 1. Hence, solutions are derived in sequence based on the range of the objective functions. In other words, the solutions with the biggest range objective function (congestion management) are calculated first, and the solutions with the smallest range objective function (negative market profit) are lastly calculated. The reason that the negative value of the market profit is considered is that this objective function is needed to be maximized on the contrary to the other objective functions (congestion management and VSI). Note that for calculating the objective function in each iteration, the optimal power flow is performed using Matpower.

After finding the multi-objective Pareto solutions, the operator might want to select the best compromise solution [165]. Thus, the fuzzy method is used to find this solution. In the fuzzy method, firstly, a normalization method is defined to equalize the range for the three objective functions and put them between 0 and 1. This procedure is formulated as in (5.30).

$$Norm_{Z_{k,s}} = \begin{cases} 1 & Z_{k,s} \leq Z_k^{min} \\ \dfrac{Z_k^{max} - Z_{k,s}}{Z_k^{max} - Z_k^{min}} & Z_k^{min} < Z_{k,s} < Z_k^{max} \\ 0 & Z_{k,s} \geq Z_k^{max} \end{cases} \tag{5.30}$$

where Z_k^{max} and Z_k^{min} are the value of k^{th} objective function which is completely unsatisfactory and satisfactory to the decision-maker, respectively. $Z_{k,s}$ and $Norm_{Z_{k,s}}$ are the s^{th} non-dominated solution of k^{th} objective function and its normalized value which has the values between 0 and 1, respectively.

The membership function can be determined for each individual as follows:

$$\varpi_s = \frac{\sum_{k=1}^{N_Z} \omega_k \times Norm_{Z_{k,s}}}{\sum_{i=1}^{N_s} \sum_{k=1}^{N_Z} \omega_k \times Norm_{Z_{k,i}}} \tag{5.31}$$

where N_s and N_Z are the number of non-dominated solutions and objective functions, respectively. ϖ_s is the membership function of s^{th} non-dominated solution. ω_k is the weighting factor of k^{th} objective function. For calculating the best compromise solution, in this chapter, the weighting factor for each objective function is assumed to be the same which is equal to 0.33. This means all the objection functions have the same importance for the decision-maker. The solution with the maximum membership ϖ_s is the best compromise solution [165]. The procedure is also shown as a flowchart in Fig. 5.3.

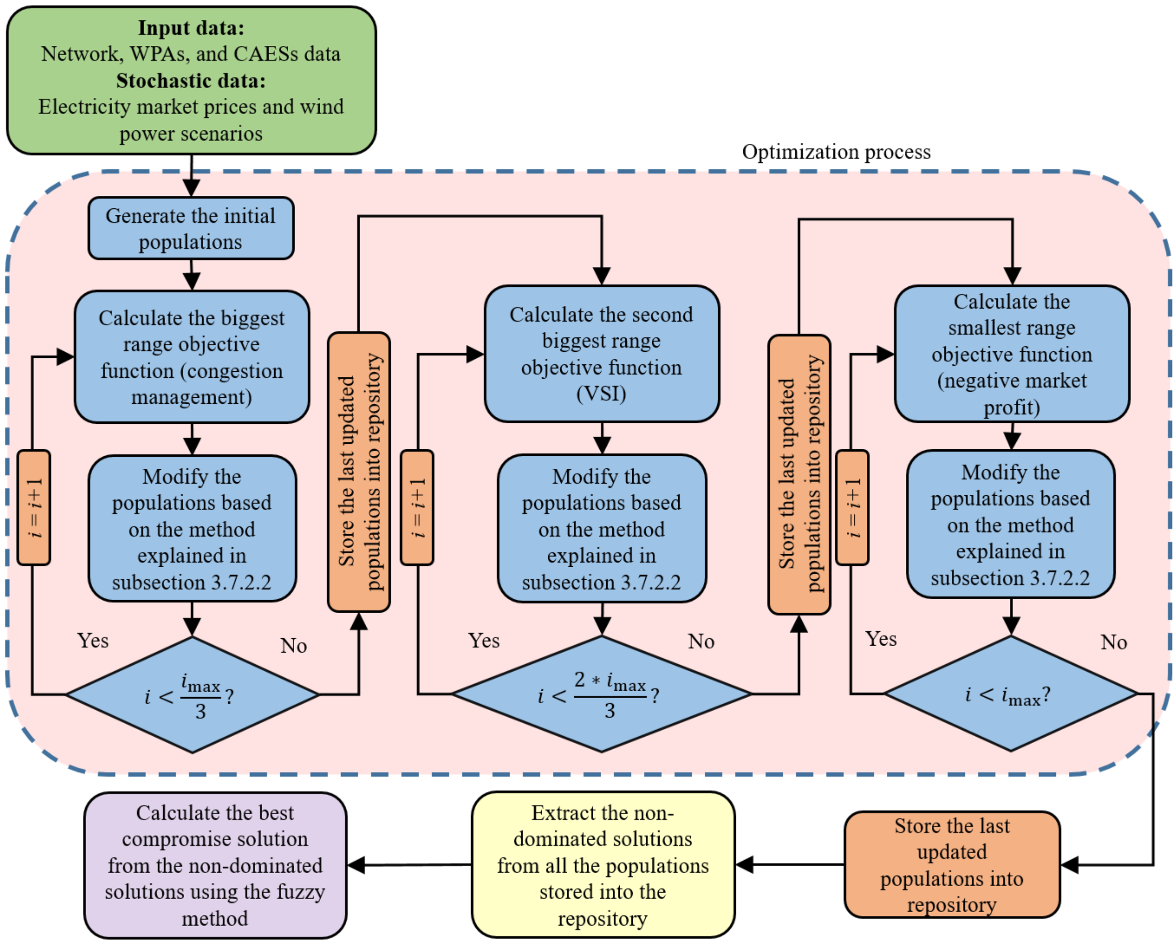


Fig. 5.3 The optimization framework

An enhanced Jaya algorithm called LJaya-TVAC algorithm, which is based on time-varying acceleration coefficients and learning phase introduced in Teaching-Learning-Based Optimization (TLBO), is used in this chapter to solve the optimization problem. Jaya is a powerful algorithm based on the conception that the new solution moves in the direction of the previously found best solution and escapes from the worst one. Jaya algorithm only needs the common control parameters and has no algorithm-specific control parameters. However, for higher convergence rate, variable coefficients and the learning phase in TLBO is added to the Java algorithm. The detail about the Java and LJaya-TVAC algorithm is available in [21, 26].

5.3 Results

The 57-bus test system is used in this chapter to test the proposed approach which consists of 7 generator units at buses 1, 2, 3, 6, 8, 9 and 12. The data related to the 57-bus test system can be found in [166]. The network in which the HPP including WPA and CAES aggregator is tested is shown in Fig. 5.4. In this figure, the red and blue circles indicate the CAES and wind power plants, respectively. The proposed methodology aims to coordinate a CAES aggregator with a WPA as an HPP to participate in the DA electricity market. The CAES is equipped with a simple cycle mode operation. The wind power and DA market price uncertainties are modeled using the scenario generation and reduction method which are explained as follows: N_1, and N_2 scenarios are generated for wind power generation, and DA market price, respectively. These uncertainty sources are independent uncertainty parameters, Also, the symmetric scenario tree is implemented to construct $N_S = N_1 \times N_2$ scenarios based on the wind power and DA market price scenarios. The presented procedure is applied to the Sotavento wind farm [28] located in Spain. The artificial neural network is trained by the wind power real data records of the year 2010. The scenarios related to market prices are obtained by the following procedure: Firstly, the prediction of DA market price for 30 days is derived by an adapted hybrid neural network and an improved Jaya algorithm [21, 29]. Secondly, the estimation of the error probability distribution function (PDF) is calculated for each hour. Finally, based on this estimation, a large number of scenarios are produced by applying the roulette wheel mechanism. Also, the scenario reduction method is employed to diminish the number of scenarios by removing the similar scenarios in addition to very low probable scenarios using the fast forward algorithm [30].

The proposed method is applied on six aggregated wind farms with 7 MW capacity for each. The stochastic wind power generation is modeled using the procedure presented in Section 3.6. Each of the 6 CAESs shown in Fig. 5.4 has a maximum capacity of 15 MW. The required heat rate of CAES for discharging mode is considered to be 0.4185, and twice this amount is considered for the simple cycle mode. The natural gas price is 3.5 €/GJ. The variable operation and maintenance cost of expander and compressor are equally considered to be 0.87 €/kWh. The minimum and maximum levels of air storage in the cavern are 1 and 15 MW, respectively. Also, the initial level of air stored in the cavern is considered to be 1 MW. The energy ratio of CAES is 0.95. In order to solve power flow in transmission networks, the MatPower package, which is a set of M-files, is used. The MatPower package is a power system simulation tool that is very simple to understand and use, and it is developed to provide the best possible performance.

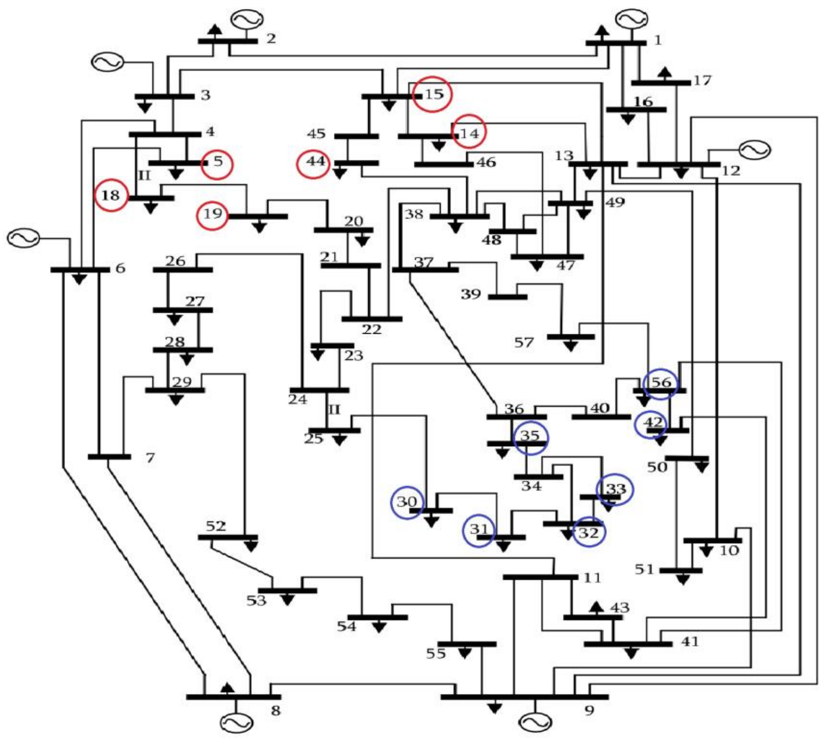


Fig. 5.4 Diagram illustration of system configurations.

Fig. 5.5 demonstrates the non-dominated and best compromise solutions for the pitch angle control and charging and discharging levels of CAESs and WPs that are optimally achieved by JAVA algorithm for three objective functions including congestion management, voltage stability enhancement, and market profit maximization. Also, As shown in the figure, the best compromise solution is designated by a bigger blue star. This solution is obtained using the fuzzy method, which is explained in more detail in Section 5.2.3. In the solution that is best for congestion management, the amount of market profit, which includes WPA and CAES aggregator, voltage stability index and congestion are 74750, 0.99950752 and 174.6096, respectively. In the solution that has the maximum market profit, the amount market profit, voltage stability index and congestion are 79787, 0.99950659 and 178.0979, respectively. Also, in the solution that the voltage stability has the minimum value, which is the best one, the amount of market profit, voltage stability index and congestion are 77322, 0.99950648 and 177.7645, respectively. For the best compromise solution, the amount of market profit, voltage stability index, and congestion are 77223, 0.99950720 and 175.8644, respectively. These values are compared in Table 5.1. In order to clearly see the objective functions' values, Fig. 5.5 is also shown in two dimensions in Fig. 5.6 to Fig. 5.8.

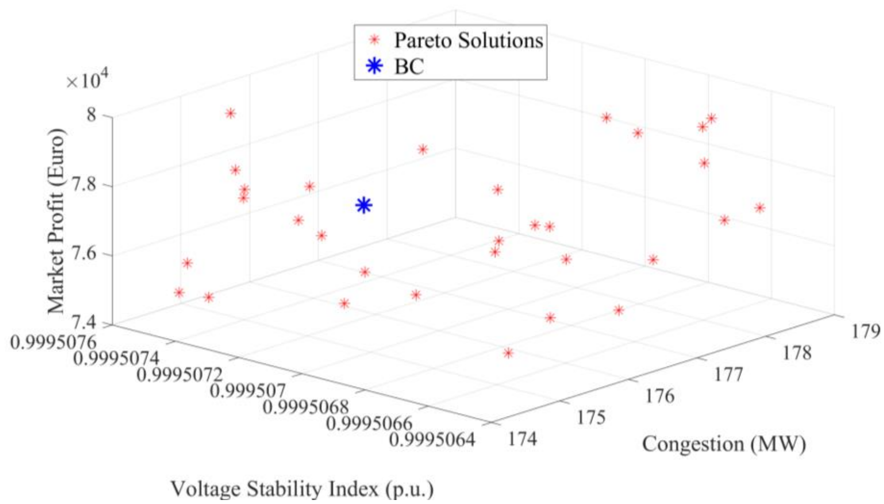


Fig. 5.5 Three-dimensional Pareto front of non-dominated and best compromise solutions of the pitch angle control and charging and discharging levels of CAESs and WPs for market profit, voltage stability index, and congestion.

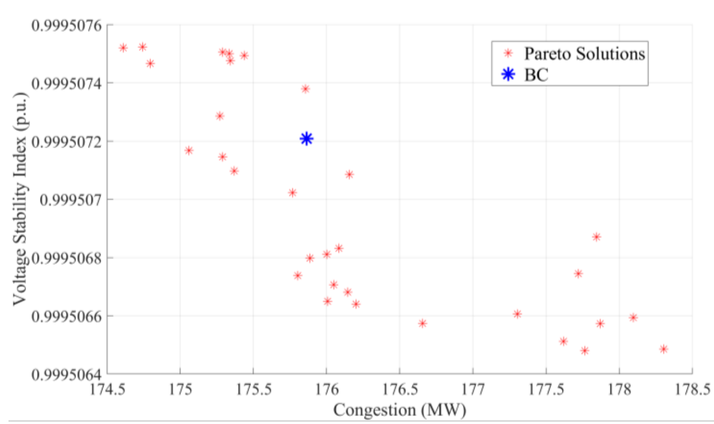


Fig. 5.6 Two-dimensional Pareto front for voltage stability index and congestion.

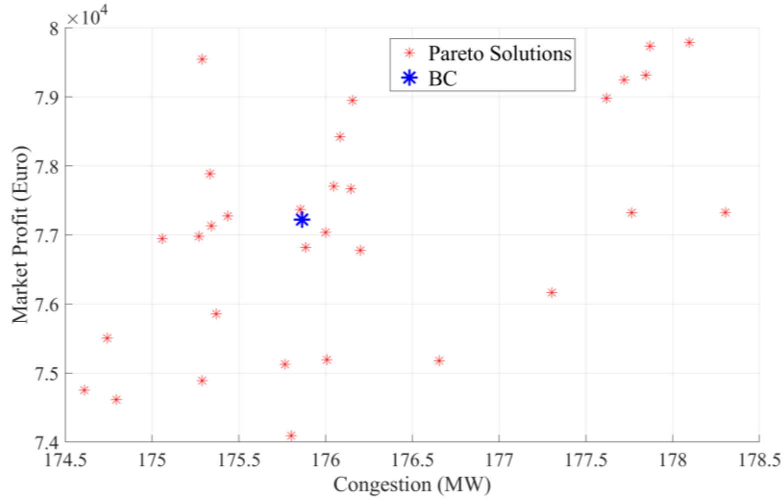


Fig. 5.7 Two-dimensional Pareto front for market profit and congestion.

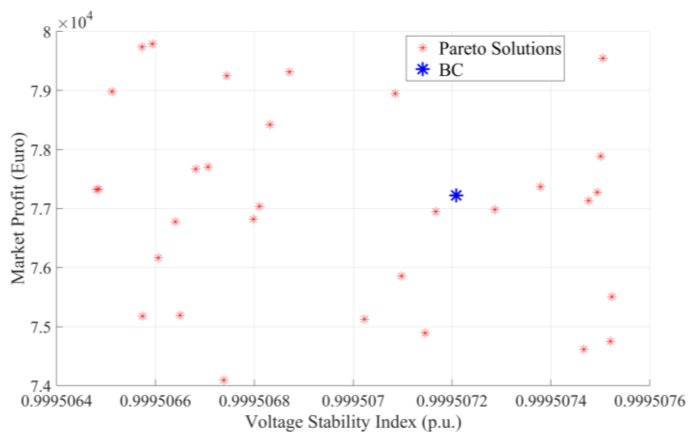


Fig. 5.8 Two-dimensional Pareto front for market profit and voltage stability index.

Table 5.1 Congestion management index, voltage stability index, and market profit value for the best solutions for each and the best compromise solution

	Market profit	Voltage stability index	Congestion management index
Best compromise solution	74750	0.99950752	174.6096
Maximum market profit	79787	0.99950659	178.0979
Best voltage stability index	77322	0.99950648	177.7645
Best congestion management	77223	0.99950720	175.8644

The obtained optimal schemes of CAES caverns' charging/discharging for all installed CAESs are shown in Fig. 5.9 to Fig. 5.12. The objective function to be optimized for Fig. 5.9 is the minimum congestion. The negative values of this figure signify the charging of the cavern, whereas the positive values indicate the discharging. Fig. 5.10 shows the optimal CAES caverns' charging and discharging of the 6 installed CAESs for the minimum VSI as the objective function. In order to have a better stability boundary, the demand load needs to be locally served [167]. The maximization of electricity market profit is the objective function for Fig. 5.11. The variation of charging and discharging of the cavern is mostly associated with the variation of the hourly electricity prices. Fig. 5.12 shows the optimal CAES caverns' charging and discharging for the best compromise solution. As mentioned before, all the objective functions are equally optimized using a fuzzy method to achieve the best compromise solution. Finally, Fig. 5.13 shows the aggregated value of all CAESs, which is the optimal power bids of CAES aggregator in the DA market for different objective functions, and best compromise solution.

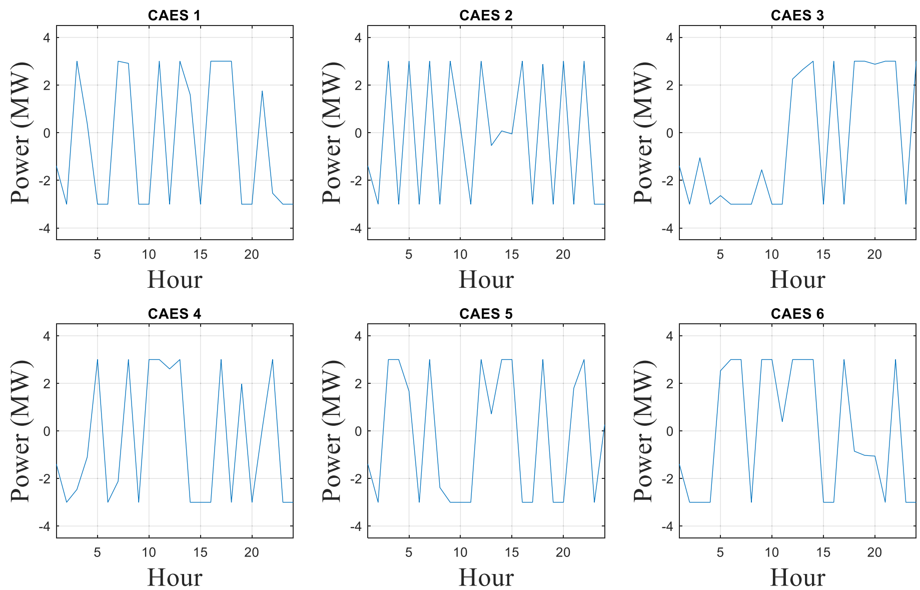


Fig. 5.9 CAESs charging and discharging for minimum congestion solution.

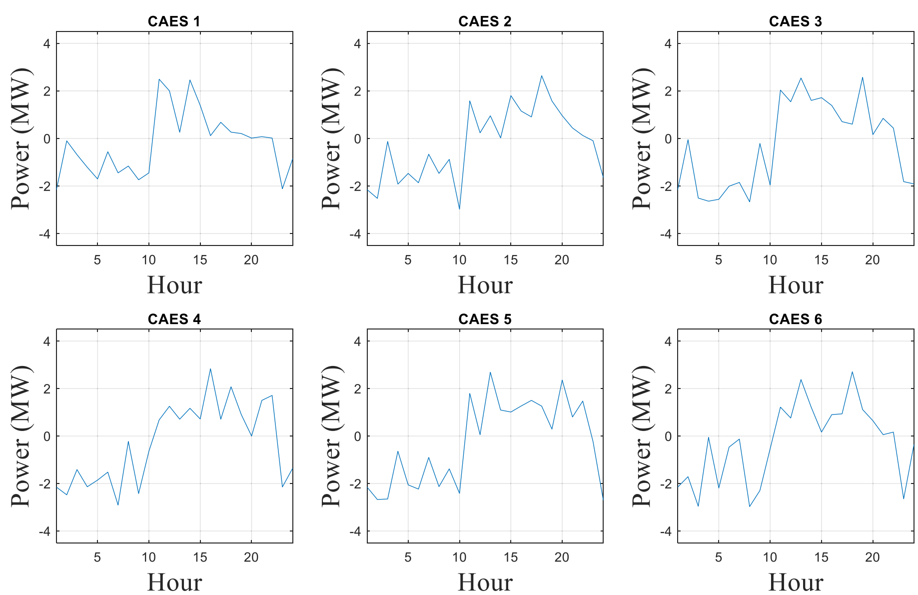


Fig. 5.10 CAESs charging and discharging for minimum VSI.

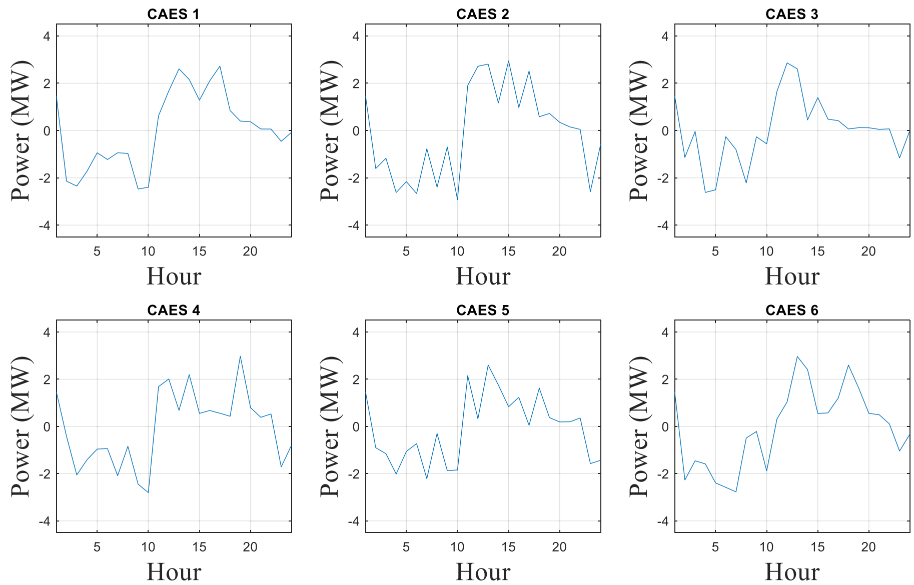


Fig. 5.11 CAESs charging and discharging for maximum profit.

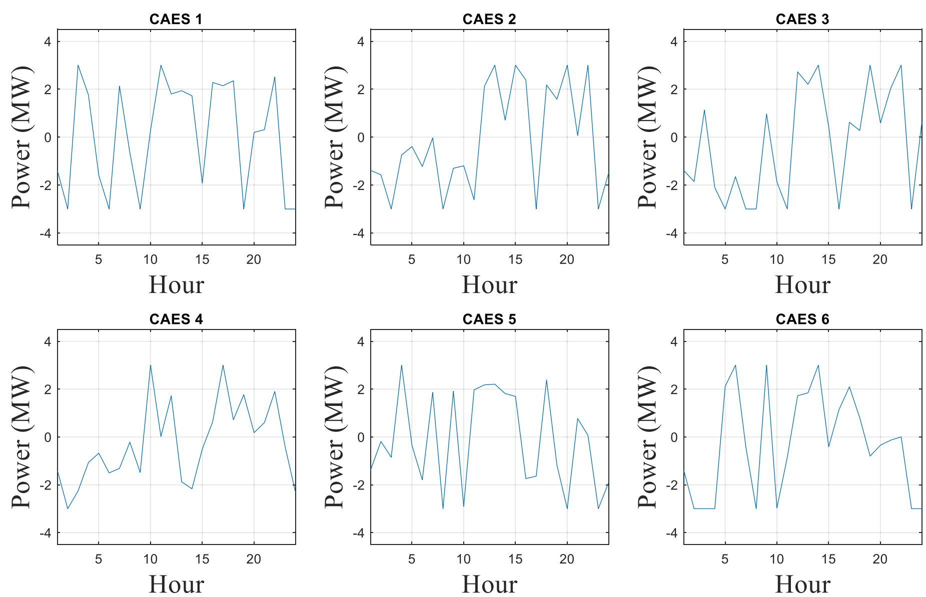


Fig. 5.12 CAESs charging and discharging for the best compromise solution.

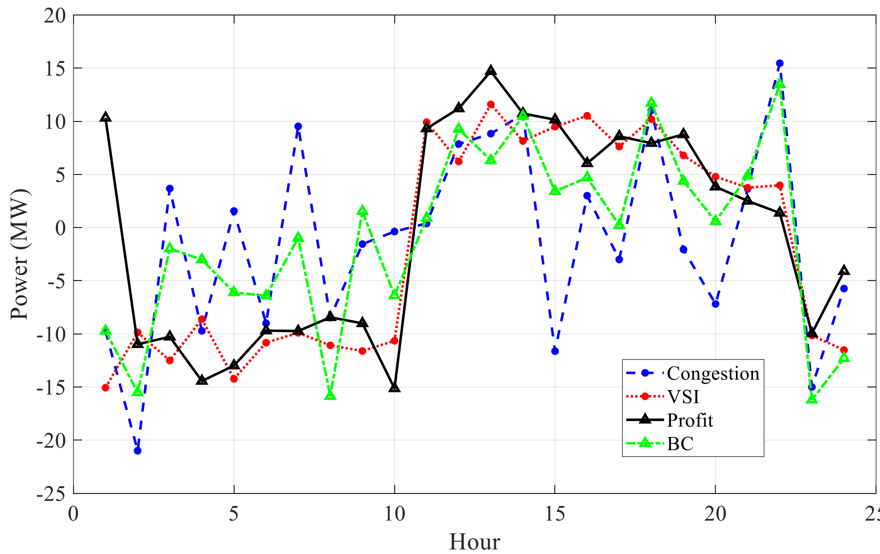


Fig. 5.13 Optimal power bids of CAES aggregator in the DA market for different objective functions (Congestion management, VSI, Profit maximization,) and best compromise solution.

Fig. 5.14 also shows the optimal power bids of the HPP in the DA market for different objective functions and the best compromise solution. As seen from the figure, for the best solution for market profit, the HPP prefers to sell the electricity in peak hours which are more expensive.

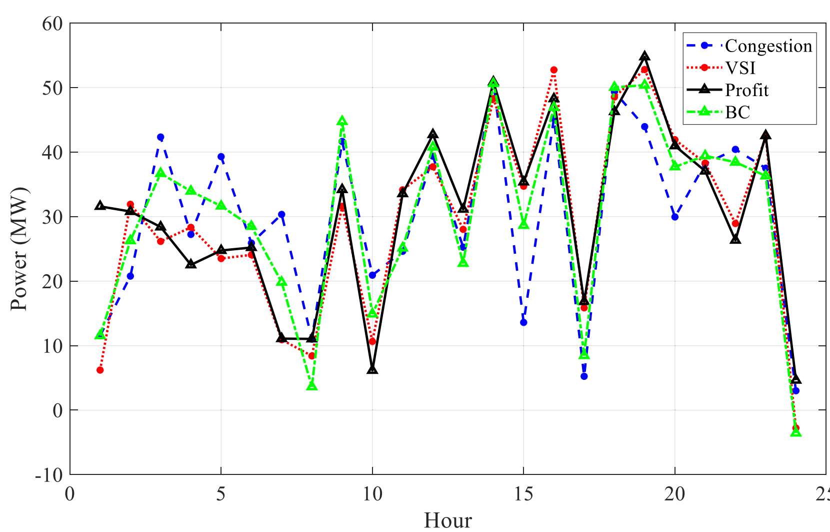


Fig. 5.14 Optimal power bids of CAES aggregator and WPA in the DA market for different objective functions (Congestion management, VSI, Profit maximization,) and best compromise solution.

Fig. 5.15 shows the network voltage stability profile during the 24-hour time horizon. According to this figure, the worst voltage stability happens at hour #5. Furthermore, the bus-VSI profile at hour #5 and the worst bus-VSI are shown in Fig. 5.16. The worst bus-VSI happens at bus 26 (bus 31 considered as the generator bus) with the value of 0.99950734 p.u.

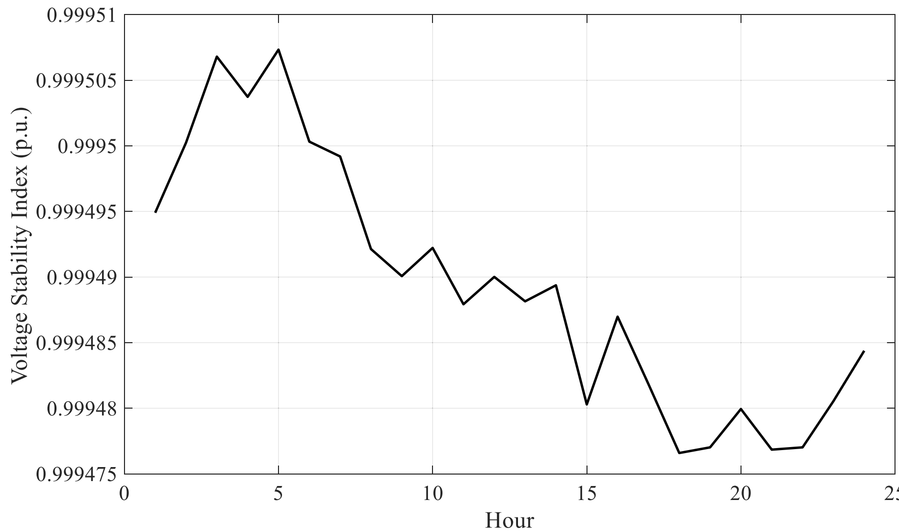


Fig. 5.15 VSI during the 24-hour time horizon.

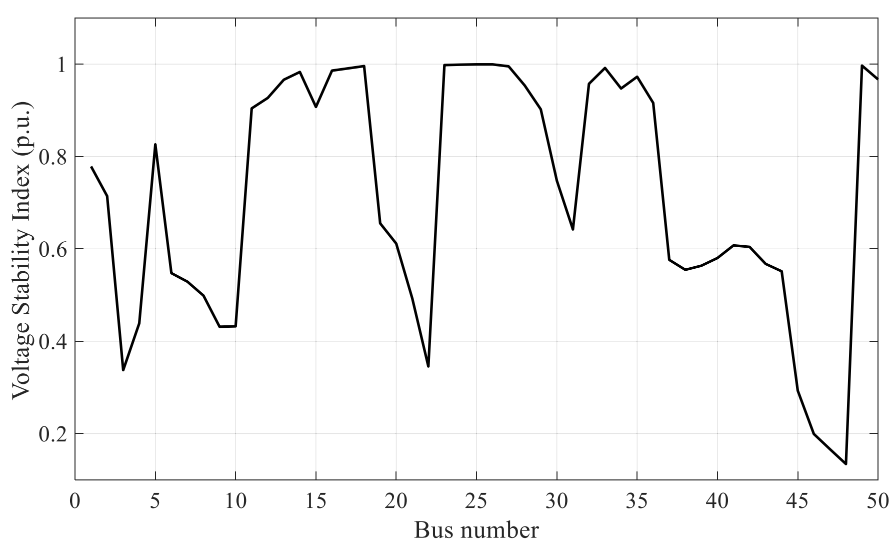


Fig. 5.16 The bus-VSI profile at hour #5.

The hourly wind curtailment levels for four solutions including the best solution for congestion management, the best solution for VSI, the best solution for electricity market profit and the best compromise solution are shown in Table 5.2 to Tanle 5.5. The wind curtailment level for each wind power generator at each hour is obtained from the results of the optimization problem. The total wind curtailment level of the best solution for congestion management is the smallest among the other mentioned solutions with the value of 573. The total wind curtailment level of the best solution for profit maximization is 589. The total wind curtailment level of the best solution for VSI is 585. Also, the total wind curtailment level of the best compromise solution is the largest among the other mentioned solutions with the value of 594. It can be seen from the results that even though the wind power is totally free, there are intervals in which WPAs are not permitted to inject the entire obtainable wind powers to the network and sell to the electricity markets. The reason is that for satisfying objective functions other than market profit maximization such as congestion management, the wind power generation needs to be curtailed for some hours in which some wind generators produce more than enough such that some lines are to be congested.

Table 5.2 Wind curtailment level of the best solution for congestion management objective function.

Hour	WP 1	WP 2	WP 3	WP 4	WP 5	WP 6	WP 7
1	7	1	1	1	1	7	7
2	1	1	1	1	7	7	1
3	1	7	1	7	1	7	1
4	7	1	7	1	7	7	7
5	7	6	1	1	1	1	7
6	7	7	7	7	1	7	7
7	1	7	7	1	3	1	1
8	7	1	7	1	1	3	7
9	1	7	1	1	7	1	1
10	1	7	7	1	1	5	1
11	7	7	1	7	7	7	7
12	1	1	7	7	7	7	1
13	7	2	7	2	1	6	7
14	1	1	7	1	7	7	1
15	7	1	7	1	7	4	7
16	1	7	7	1	1	1	1
17	6	1	7	7	1	1	6
18	1	7	2	1	1	7	1
19	1	1	7	1	1	4	1
20	7	7	7	1	7	7	7
21	1	7	1	7	7	7	1
22	1	7	7	1	7	7	1
23	1	1	7	7	1	1	1
24	1	1	1	2	7	7	1

Table 5.3 Wind curtailment level of the best solution of VSI objective function.

Hour	WP 1	WP 2	WP 3	WP 4	WP 5	WP 6	WP 7
1	2	4	5	4	2	5	2
2	1	2	6	3	7	3	1
3	4	3	7	4	6	2	4
4	6	5	6	7	6	6	6
5	3	5	3	7	3	7	3
6	2	1	6	7	2	2	2
7	5	7	4	1	2	6	5
8	1	5	2	6	7	2	1
9	5	1	5	1	4	7	5
10	1	3	1	1	1	2	1
11	3	7	2	2	2	5	3
12	3	7	1	4	3	5	3
13	6	2	4	7	2	7	6
14	2	1	2	3	2	6	2
15	5	7	3	6	6	4	5
16	5	3	4	4	6	1	5
17	2	5	6	2	5	3	2
18	3	3	5	5	5	2	3
19	7	6	3	4	6	5	7
20	5	6	7	7	2	3	5
21	7	5	2	4	1	6	7
22	3	2	7	4	3	7	3
23	5	4	3	2	1	6	5
24	2	6	3	5	7	7	2

Table 5.4 Wind curtailment level of the best solution of profit maximization objective function.

Hour	WP 1	WP 2	WP 3	WP 4	WP 5	WP 6	WP 7
1	7	2	3	2	1	6	7
2	5	2	6	4	4	3	5
3	2	4	6	4	4	2	2
4	6	2	5	1	3	1	6
5	5	3	3	6	3	4	5
6	6	4	7	4	5	5	6
7	5	2	4	2	6	5	5
8	7	6	4	2	7	7	7
9	3	2	3	7	3	1	3
10	3	4	5	1	6	4	3
11	2	3	7	7	5	4	2
12	5	6	3	3	3	5	5
13	2	5	4	6	7	6	2
14	4	3	2	6	2	4	4
15	4	5	5	1	7	2	4
16	6	6	7	4	7	7	6
17	6	6	6	2	4	1	6
18	2	7	2	1	3	1	2
19	5	1	3	3	7	3	5
20	1	2	3	7	5	1	1
21	3	3	6	6	1	5	3
22	1	7	5	3	6	7	1
23	5	5	5	1	5	3	5
24	3	6	2	4	6	5	3

Table 5.5 Wind curtailment level of the best compromise solution.

Hour	WP 1	WP 2	WP 3	WP 4	WP 5	WP 6	WP 7
1	7	4	4	1	1	1	7
2	6	2	1	1	7	7	6
3	2	7	7	6	1	7	2
4	1	2	5	4	7	5	1
5	5	5	1	3	1	5	5
6	7	7	6	5	1	6	7
7	1	7	7	3	7	1	1
8	6	1	7	6	7	7	6
9	4	1	1	1	6	2	4
10	1	5	6	1	1	4	1
11	4	4	1	7	2	7	4
12	7	7	7	7	3	2	7
13	5	5	1	7	3	1	5
14	1	1	7	3	7	3	1
15	3	6	5	1	1	2	3
16	1	7	7	5	6	7	1
17	6	3	2	1	4	5	6
18	5	5	7	1	1	4	5
19	1	6	5	1	3	1	1
20	5	7	7	1	7	7	5
21	1	6	3	5	4	5	1
22	2	7	7	1	7	4	2
23	1	6	7	7	5	2	1
24	2	7	3	1	5	7	2

5.4 Summary

This chapter has modeled an HPP considering network WPA. The wind generators are equipped with pitch angle control ability to adjust the wind power curtailment level. In order to analyze the effects of the network constraints, two additional objective functions including congestion management and voltage stability improvement have been considered, and multi-objective Pareto front solutions have been used to optimize all the objective functions simultaneously. The results show that these two additional technical objectives conflict with the profit maximization in the electricity market. This method is used in the time that the market player gets benefit or incentive from the network owner by bringing congestion management and voltage stability indices to a specific point.

In this chapter, two different technical objectives from the perspective of the power grid were considered. The problem can also be solved in future work based on other objectives such as power losses and voltage profile of the network.

6 Conclusions and Suggestions for Further Work

In this chapter, an overall review of the contributions and the important possible areas for further research are reviewed and briefly summarised.

6.1 Summary and Conclusions

A literature review of existing HPP and its operating systems was presented in Chapter 2. In this chapter, different types of HPP, including technical and commercial ones, have been investigated. Several kinds of electricity markets, including pool and future markets, have been introduced and discussed in detail. HPP components which include flexible loads, energy production and storage units have been presented. Furthermore, the fundamentals of stochastic programming and risk management have been briefly reviewed.

The contributions of Chapter 3 have included: 1) the development of a two-stage stochastic decision-making model for the participation of CAES aggregator equipped with a simple-cycle mode operation which gives it the ability to work as a gas turbine in both DA and intraday markets. 2) the development of an optimal offering strategy model for the joint operation of a WPA and a CAES aggregator as an HPP to maximize their expected profit and also to mitigate wind power uncertainties. 3) the implementation and analysis of the proposed framework on three different electricity markets in a realistic case study. 4) offering a robust risk constrained HPP model to overcome the financial risks of electricity markets.

Chapter 4 has proposed an approach for the joint operation of a WPA and a DRA as an HPP in which the WPA has utilized the DRA as a storage facility. The HPP has participated in the DA, intraday, and balancing markets. The uncertainties of wind generator production, their outage, and market prices of three markets have been considered. In order to find the best offering strategy, the stochastic programming method has been used, and then the CVaR has been added to control the financial risk.

Chapter 5 has modeled an HPP considering network constraints. The HPP also has included a CAES aggregator with a WPA. The wind generators are equipped with pitch angle control ability to adjust the wind power curtailment level. In order to analyze the effects of the network constraints, two additional objective functions including congestion management and voltage stability improvement have been considered, and multi-objective Pareto front solutions have been used to optimize all the objective functions simultaneously.

Overall, this thesis has investigated three major technical studies in the form of an HPP. The first two technical chapters (Chapters 3 and 4) only focused on the financial aspect of an HPP, while the last technical chapter (Chapter 5) considered the technical aspect and power quality in the electricity network. In Chapters 3 and 5, the HPP includes a WPA and CAES aggregator, while in Chapter 4, the HPP is comprised of a WPA and DRA.

6.2 Future work

In this thesis, several models for implementation of HPPs were developed, and their participation in power markets and their effects on power networks were explored. The current research can be extended in several ways, mainly:

- Future power grids will be equipped with various technologies, for example, the various kinds of renewable generations. Therefore, HPPs can involve a more diverse set of participants. A future research direction can be studying a comprehensive model that includes PV, wind generation, DGs, different kinds of storage systems, electric vehicles, and DR at the same time.
- In Chapters 3 and 4, the pool market including DA, intraday, and balancing markets were considered. The participation of HPP in other markets such as future, reserve, and regulation markets and bi-lateral contracts for DRA is an interesting topic which can be investigated in future studies.
- In Chapters 3 to 4, stochastic programming was used for modeling the uncertainties which require several years of historical data for generating scenarios. When there are not enough historical data available, some other types of methods such as robust optimization or information gap theory can be used to model the optimization problem.
- Other novel or improved models of wind generation, CAES, and DR can be used. For example, a more realistic and accurate DR model can be utilized by considering the elasticity of customers or clustering the customers based on their real data into several groups.
- In Chapter 5, two different technical objectives from the perspective of the power grid were considered. The problem can also be solved based on other objectives such as power losses and voltage profile of the network. Similar to the study in Chapter 5,

sometimes these technical objectives might conflict with the profit maximization in the electricity market.

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