Signal Processing and Renewable Energy
March 2021, (pp. 15-40)
ISSN: 2588-7327
eISSN: 2588-7335

Maximizing Energy Storages Revenue Using Two-Level Model and Considering High Influence of Wind Resources and Market Balance Constraints

Mojtaba Najafi[1*], Sadegh Derakhshan[1]

[1] Department of Electrical Engineering, Bushehr Branch, Islamic Azad University, Bushehr, Iran.

Received: 17-Sep-2020, Revised: 23-Oct-2020, Accepted: 27-Oct-2020.

Abstract
In this paper, a method is presented to maximize the revenue from price difference due to the presence of storage systems in the power system with a high penetration level of wind resources. To account for price changes due to the profitability of price differences, a two-level model is presented that maximizes the earnings from price differences and has been carried out at a low level of market-clearing procedure. The high level uses low-level production prices and adjusts the storage outputs that affect the low-level price. Conversion techniques have been used for single-line programming with respect to system balance constraints. In order to check the performance, the proposed method will be implemented on the IEEE 118 bus test network. Analyzing the results revealed that the proposed method has improved significantly compared with the traditional method and has been able to achieve higher arbitrage income. By applying a two-level model can soften clearly the marginal price by lowering the price at peak times and raising it at non-peak times and the storage's charging power of the traditional model is much lower than that of the two-level model at low marginal hours. The results show that proposed algorithms can increase revenue from traditional to two-level models from $ 43280 to $ 65700, respectively.

Keywords: Storage, Arbitrage, Maximizing Income, Wind Energy.

1. INTRODUCTION

In recent years, the electricity industry has faced a dramatic increase in the use of non-dispatchable energy sources. This dramatic use has reduced costs and environmental problems. Of course, despite the many benefits, these resources pose challenges for

***Corresponding Authors Email:** mojtabanajafi2000@gmail.com

designers and researchers. Storage systems are used to enhance system flexibility to address problems such as resource uncertainty. Based on hourly price differences, these systems absorb energy at off-peak hours and network it at peak hours, leading to profitability from price differences. This exploitation of storage systems is particularly useful in systems with a high level of resource penetration in the power shifting role. Studies on storage systems are divided into long-term and short-term categories, which long-term studies focus on sizing strategies, position design and revenue assessment, and short-term studies focus on day-to-day maximization strategies in real-time and real-time markets. In the long-term run, profits from price differences are usually estimated annually. Basically, the profitability of the price differences for the storage depends on the price differences over time. Charging occurs when marginal prices are low and discharge occurs when prices are high, which storage system reduces the margin of profitability resulting from price differences. This is because the storage system monitors load changes in the profitability situation caused by price differences and minimizes drastic price changes through pickup and filling. Renewable energy products have low energy costs and high power fluctuations, which further exacerbate price changes and cause sharp market price jumps. Connecting renewable energy sources has increased the power quality challenges of traditional power systems [1]. Dispatching variable power sources increases power supply Disconnections, increasing the risks of continuous fluctuations in network sability [2]. Some recent reports demonstrate an increase in the share of renewable energy sources in total European and US electricity production over the years to come [3]. Most existing sources of thermal power generation do not respond to unexpected sudden changes in variable sources [5 and 4]. This has led power system users to provide solutions to stabilize the network against production changes. Storage systems are one of the most flexible resources in the power system which is a solution to undo these changes [6]. Energy storage systems are divided into three categories: small, medium, and large according to different applications [8 and 7]. Because the exploitation of renewable sources has created challenges in the power fluctuations that make power system equipment difficult [9]. The storage systems are capable of recovering the voltage by the reactive power supply and enable thermal generators to track their timed output in terms of baseload values [10]. Storage systems are particularly popular among power system users because of the improved power quality [11]. Some studies focus on the characteristics and utilization of different storage technologies. Other researchers are studying the modeling and sizing of energy requirement-based storage systems for unlimited power grids. However, there is a need to provide a way to choose the best storage technology to be present in the confined power grid and the competitive electricity market.

Energy storage systems are of great importance because of their integration with renewable energy sources and the elimination of their challenges. In addition, supplying large volumes of stored electricity has made these resources extremely efficient in power systems. Using storage systems in high penetration of cross-sectional sources, improving network reliability by increasing transmission capacity and improving power quality by eliminating voltage fluctuations are the most important applications of storage systems. Storage systems are also cost-effective. They do not have rotary storage systems, so their maintenance costs are lower and their troubleshooting is easier and faster [12]. The addition of many renewable energy sources causes more voltage flickers and more frequency fluctuations. Traditional power stations are operated on a timed basis to meet demand in terms of peak load information. The effects of renewable power stations in this situation should be controlled using storage resources. In order to use electricity generated by wind power plants, a certain amount of electricity from other sources must be available to maintain the grid's stability. This is an important issue highlighted by European countries such as Spain and Denmark. The storage system can be used to prevent the installation of new production capacity required [13]. The storekeeper stores any unused electricity from solar and wind power plants during low load hours and delivers low power output. The storage system supports photovoltaic systems in recovering voltage drop under cloudy weather conditions resulting in soft output [14]. The loads on each network are not always constant and vary at different times of the day and year. Courier demand is normally seen at every hour of the day and season to ensure the required amount of demand is generated. To meet demand during peak hours, the cost of electricity increases. In order to prevent the exploitation of these non-economic power products, the storage systems can be used to save electricity during off-peak hours and to provide during the productive hours, which helps reduce costs and build new power plants. The decline in traditional production during peak hours also results in a reduction in greenhouse gases [15]. Storage systems are useful for recovering the voltage of generators connected to the grid during a fault in the near grid. This also makes it possible to reach the maximum power of generators, which normally has problems with low voltage operating conditions. Storage systems can also be used as a substitute for power compensators. Normally high voltage gradient generators are also used to compensate the voltage. The storage systems are also addressed and provide the reactive power needed to stabilize the voltage levels at specified regulatory points during sudden shortages of wind speeds. However, for faster switching, the storage system should be connected to FACTS devices or compensators such as STATCOM. Operation reserves are available to compensate sudden changes in load and power supply for the generator loss situation. Operating reserves are normally considered to be as much as the capacity of the largest generating unit on the grid. Storage systems can help replace rotating reserves to reduce fuel usage costs. The article [16] discusses the sizing of storage energy sources to counteract the voltage effects of renewable sources in distribution systems.

Another parameter that is considered in [17] is the cost of the storage system that must be taken into account. Because the large distributed storage system eliminates voltage fluctuations better than the small centralized storage system, the λ_{cost} coefficient introduces a compromise between the voltage support benefit and the storage cost. In this reference, the problem- solving method is based on a two-level optimization of genetic algorithm. Article [18] deals with the comparative study of storage devices in the grid-connected photovoltaic systems. It is noted in this reference that few studies that have simultaneously examined the capacity of hydrogen storage units and the operation strategy. Generally, grid-connected storage systems and photovoltaic systems have been studied in [19]. Storage system capacities and operation parameters are optimized simultaneously using the genetic algorithm. Article [20] deals with the sizing of energy reserves for the management of micro-grid utilization using the enhanced bat algorithm. In this reference, a cost-based formulation to determine the optimal storage size for micro-grid operation is presented. In [21], Economic Analysis, optimum sizing of the storage system in combination with photovoltaic systems is presented. This reference points out that most of the research is from a network perspective and its purpose is to optimize the part of the distribution network that needs to know the network model and input information. Article [22] discusses the optimal operation and sizing of energy storage system under dynamic pricing for the efficient integration of renewable energy sources. The reference states that the network power has a real-time and the price depends on the operating time, while the marginal cost of renewable resources is zero. [23] also deals with the issue of energy storage size in terms of uncertainty. In this reference, the energy storage system is suggested as a solution to reduce the slope of generators and peak and forecast errors compensation. Optimal sizing of the storage system is considered as the main issue of this reference. [24] also deals with spatial modeling of wind production for optimal sizing of storage system. In this reference, appropriate random power modeling of wind power is discussed to model the uncertainty observed in the wind data. [25] also presents a probability-based approach for optimizing the storage resources in the presence of photovoltaic systems and household appliances. In this reference, the proposed instrument inputs include home load profiles and solar radiation information, and outputs include total load profiles with and without energy management for various storage and photovoltaic installation capacities. In [26], a robust model predictive control (RMPC)-based bidding strategy for wind-storage systems is used to increase their revenue in real-time energy and regulation markets. [27] presents a decision framework for respecting the market constraints and maximizing the revenues of a wind-storage based hybrid power plant. Ref. [28], presents a novel model to optimize the bidding strategy of a wind farm coupled with a high-temperature heat and power energy storage system (based on different designs) in the energy market. [29] uses case for the mobile battery storage converting curtailed wind energy into an asset is investigated.

For this reason, in this paper, we intend to focus on the studies of price differences resulting from the presence of storage systems in the power system with a high level of penetration of wind resources. To account for price changes due to the profitability of price differences, a two-level model is presented that maximizes the revenue from price differences and at a low level, there will be a market-clearing procedure. The high level uses low-level production prices and adjusts the storage system outputs that affect the low-level price. We will use conversion techniques for single-line programming concerning for to system equilibrium constraints. The proposed method will be implemented on the IEEE 118 bus test network. The innovation aspect of this paper is based on maximizing the income from price differences due to the presence of storage systems in the power system with a high level of penetration of wind resources, which has been less discussed in the articles. Two-level modeling based on high-level and low-level is used, which is the latest optimization method. At the highest level, maximizing revenue from price differences will be done and at the lower level, the market-clearing procedure will be implemented. We will also use conversion techniques for single-line programming with respect to system balance constraints.

2. GENERAL DESCRIPTION OF THE ARBITRAGE FRAMEWORK

To determine the amount of energy storage arbitrage, various methods are used, such as the economic feasibility method, which compares the annual income requirements with the investment cost to the arbitrage income probability. The amount of arbitrage is separated from other services. Due to the complexity of the analysis, estimating the amount of arbitrage work is complex. The economic feasibility of energy arbitrage is defined by the financial flow when the total revenue from the arbitrage service exceeds the cost recovery requirements.

The following relationship indicates the main parameters of the financial flow [26].

$$-\left(pd_0 p_0\right)+\left(\mathrm{P}\eta d_0 p_p\right)D > \left(PC_{Sto}d + PC_{PCS}\right)\alpha \tag{1}$$

In the above relation, P is the storage capacity per kW, η is total storage efficiency, d is the storage time to maintain output power at P rated capacity per hour, d_0 duration of storage capacity at rated capacity P in hours per day, D denotes the number of days of storage operation per year, P0, Non-peak price in dollars per MWh, p_p , peak Hour-prices in US dollars per MWh, C_{Sto} is the incremental cost of the power saver in dollars per kWh, C_{PCS} is the incremental cost of the power electronics storage system, and the annual cost alpha factor.

Assuming the energy storage system operates daily throughout its period, $d = d_0$, and by resetting the above equation to solve the C_{Sto} investment cost, we will have:

$$p_0\left(-1+\frac{\eta p_p}{p_{\ 0}}\right)+\frac{D}{\alpha}-\frac{C_{PCS}}{d} > C_{Sto} \tag{2}$$

Assuming that the incremental cost associated with power electronics is known, the incremental cost required to store is a function of the non-peak price, the difference between the pick and non-peak price expressed as a ratio, and the efficiency, number of days of operation, and annualization factor.

2.1. Real Time Energy Arbitrage in the Market

In [30] a temporary arbitrage policy for energy storage systems using robust learning. Real-time price arbitrage is provided and it is an important source of revenue for storage units, but designing appropriate strategies for these revenues is a complex task due to the highly uncertain nature of prices. Instead of linear forecasting or scheduling methods, Robust learning has been used in [30] to design optimal arbitrage rules. These rules are learned by repeating the charging and discharging procedures by updating the corresponding matrix. In this reference, a reward function that reflects the immediate benefits of charging and discharging decisions and includes the share of historical information is presented.

In [31], the problem of optimizing energy arbitrage for a linear piecewise cost function for energy savers is solved using linear programming. The linear programming formulation is based on epigraph minimization. [32] discusses the opportunities available in the day-ahead markets and the real time for storage arbitrage. This reference points out that the power storage system is a unique system in the network capable of providing multiple services. These services are categorized based on charging and discharge profile specifications. Energy applications are usually extended over long periods of time and power applications are shorter in time scale and are used for network stability. [33] presents a method for the optimization of combined stochastic robustness for energy storage arbitrage in real-time and day-ahead energy markets. The reference points out that from a system standpoint, the storekeeper is capable of providing peak response and flexibility to cope with the uncertain environment of renewable resources, reducing losses and promoting system resilience. [34] provides a method for estimating long-term revenue for the battery in performing arbitrage and attendance services. The reference states that estimating storage revenue is necessary to analyze the financial feasibility of investing in batteries. [35] provides a multi-objective optimization of energy arbitrage in energy storage systems using different battery technologies. The reference points out that the power system requires an extra degree of flexibility to provide a platform for high-scale integration of renewables. In [36], the mean-variance-based scheduler optimization method with reference to real-time and day-ahead marginal price uncertainties is presented. In this reference, marginal prices are considered uncertain. Stock arbitrage risk associated with the uncertainty of margin price prediction is modeled through the variance component in the objective function.

Studies on the stock price arbitrage problem are divided into long-term and short-term categories based on time horizon. Long-term studies are cost analysis and include position design, storage size, and earnings assessment. Short-term studies focus on maximizing daily profits in the real-time and day-ahead markets. In long-term studies, the arbitrage benefit is estimated annually in a linear programming model in [37] with reference to the storage system lifetime. The optimal type of storage system, the configuration of capacity and the power of storage system have been studied in [38] using a linear programming model based on historical price information. Similarly, arbitrage income in the New York electricity market and its effects on storage efficiency are examined in [39]. In these studies, different models have been used to examine the different price signals for maximizing daily arbitrage.

In essence, price arbitrage refers to price differences over time [40]. Charging occurs when marginal prices are low and discharges occur when prices are high. Therefore, the storage in the arbitrage mode reduces marginal price deviations due to load changes and the storage improves the situation by using peak curve and filling curve valleys. Contrary to this situation, renewable products have low energy costs, but widespread power fluctuations that lead to price deviations and can lead to unwanted marginal price jumps. From the perspective of private storage owners, markets with high levels of renewable sources are more popular because of price deviations, lower reserve margins, and higher flexibility slope requirements. The study of the storage arbitrage is of great interest considering the effects of momentary price changes and price deviations from renewable sources.

One of the features discussed for arbitrage studies is that arbitrage models require price signals as model inputs. These models are known as price receivers. For example, linear planning based on estimates uses historical or pre-calculated prices. The robust model uses price range and the stochastic model uses price forecasts and scenario reduction methods. These models cannot directly detect the effects of storage operations on marginal prices and, ultimately, their effects on arbitrage income. Therefore, a more sophisticated model is needed for arbitrage evaluations of the storage system, especially in the case of large storage systems with significant capacities and capabilities.

Next, after modeling the market structure, the issue of storage arbitrage revenue studies can be applied to existing storage systems or used in cost-benefit analysis at the design stage. To account for price changes following arbitrage activities, a two-level model is presented to maximize arbitrage in the high-level model and the market adjustment procedure at the lower level is simulated. Rather than relying on price inputs or price forecasts, the high level uses low-level prices and adjusts the storage's output, which in turn affects the low price. Linear conversion techniques are used to reformulate the problem and state the problem as one-level mathematical programming with equilibrium constraints and finally solve the problem based on a hybrid integer linear programming. In fact, the market structure of the study is presented in accordance with the standard rules, which allows the storage owners to participate in the day-ahead market for arbitrage activities. Also, in this paper, traditional arbitrage models are generalized to the two-stage model, which includes arbitrage estimation and price forecasting. This model presents a generalized production method with wind forecasts and streamline constraints. A two-level arbitrage estimation model is presented that does not rely on price inputs and can derive marginal prices based on system production, load level, and renewable output fluctuations simultaneously. This paper will also evaluate the effects of key factors such as power and energy storage capacity, load level, and wind power capacity.

2.2 Modeling Market Structure

Arbitrage prices for large storage systems generally run in the wholesale markets of the day-ahead, ie the markets with the largest share of power supply and demand are being met in those markets. Fig.1 displays the wholesale market structure of the day-ahead with three types of contributors. Production companies and wholesale subscribers in the market are partnering with freelance marketers in offering up-to-date high-capacity bids and related demand. At a fixed time to close the market, the operator adjusts the market according to the transmission network and the dispatched levels and related prices for the next day. The role of the arbitrage partnership with the orientation of arbitrage in the market is a buyer-seller exchange. Unlike manufacturers or consumers who can bid on prices or set their preferred price for purchase, storekeepers offer their buy or sell offers at zero prices for arbitrage purposes due to low capacity. Storage price level contributors do not add buy or sell bids. These contributors can influence marginal market prices at some critical levels of the load. Unlike other market participants, the storage pays or receives an instant price for energy purchased from the market or resale. This assumption is in line with the standards of [41] to allow storekeepers to participate in wholesale markets.

2.3. Modeling the Storage Arbitrage

The main characteristic of traditional arbitrage models is that these models require price information as input, which will be required even if price information comes

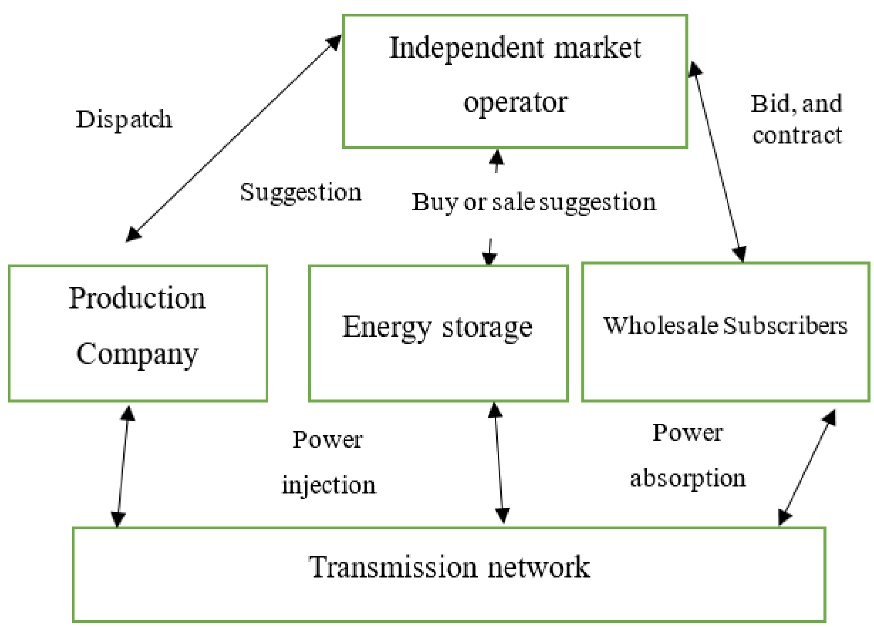

Fig. 1. Wholesale market structure of the day ahead.

from various forms such as corrected historical information, or time series forecasts. The objective function for the time interval y is formulated in relation 3, which is to maximize the arbitrage annual income and the sum of the revenue over all time-intervals. This is equal to the sum of the discharge revenue minus the recharge costs as follows:

$$Max\ R_y = \sum_t \sum_{i,[n\in\psi(i)]} \left(\pi_{n,t} * S_{i,t}\right) = \sum_t \sum_{i,[n\in\psi(i)]} \{\pi_{n,t} * \left(\sqrt{\eta_i} P_{i,t}^d - P_{i,t}^c / \sqrt{\eta_i}\right) \quad (3)$$

In the above relation, t is the time-interval index in the time horizon from t_0 to t_{0+h-1} and i is the index of the store from 1 to I. Ry denotes the income of the storage arbitrage at interval y and the s_{it} is the output power at time t seen from the network per MW. S is negative for the absorption of power and positive for the injection of it. Also, the π_{nt} is the marginal price inputs at bus n at time t, P^d_{it} and P^c_{it} are the discharge and internal charging capacities of the i^{th} storage at t time, respectively. Also, ψ (i) is the bus to which the i^{th}storage system is connected. The η_i efficiency is defined as the ratio of the energy given to the storage received energy.

This efficiency is used in place of separate charging and discharging efficiencies derived from [42]. In an ideal situation with no power losses, Ry's income is always non-negative, as the storekeeper has to sell energy at high margin prices and buy energy at low power hours.

The i^{th} storage available energy at the end of time t, is the E_{it}, which is determined by the energy remaining at time t-1, the daily discharge rate γ_i, the negative / positive energy stored / fed at time t. The energy available to the storage system is determined as follows:

$$E_{i,t} = \frac{(1-\gamma_i)}{24} * E_{i,t-1}\Delta t - \left(P_{i,t}^d - P_{i,t}^c\right)\Delta t \quad (4)$$

In this equation, Δt is the time interval between two consecutive intervals that is considered in this study.

Storage systems also face physical limitations. The most common of these limitations are the charge status (SOC) and the power limit. The SOC constraint represents the residual energy level over a given interval, namely the charge status is in terms of available capacity per percent based on nominal capacity. The storage power limit also refers to the charging and discharging capacities in nominal values. These physical constraints are expressed as follows:

$$SOC_{i,t0+h-1} = SOC_{i,t0} \quad t = 0 \quad (5)$$

$$SOC_{i,min} \le \frac{E_{i,t}}{E_{imax}} \le SOC_{imax} \quad (6)$$

$$0 \le P_{i,t}^d \le \alpha_{i,t}^d P_{imax}^d \quad 0 \le P_{i,t}^c \le \alpha_{i,t}^c P_{imax}^c \quad (7)$$

$$\alpha_{i,t}^d + \alpha_{i,t}^c \le 1 \quad (8)$$

In the above equations, SOC_{it0} and $SOC_{it0+h-1}$ are the starting and ending states of the charging respectively. SOC_{imin} and SOC_{imax} are high and low charge status constraints. E_{imax} is the Power Capacity and P^d_{imax} and P^c_{imax} are the nominal values of the discharge and charge respectively. α^d_{it} and α^c_{it} are also discharged and charged in binary displays, respectively.

The traditional arbitrage model, expressed in equations 3 to 8, is a linear programming. This model takes the marginal price of π_{it} as input and hence, the model is strongly dependent on this parameter. The solution to this problem generates arbitrage income during the period under study and provides the power outlet pattern for achieving the desired income. This model is applicable to arbitrage-free storage capacities that are too small to affect marginal prices.

The traditional model of storage arbitrage has three main problems. The first problem with this model is that it is not applicable to large-scale storage devices, where their outputs affect market clearing prices [43]. The second problem with this model is the lack of power line constraints that cannot be limited without generator information, network and loads. This enables storage systems to utilize their power output to the maximum possible amount at any time and to generate unavailable revenues at high capacities. The third problem with the traditional arbitrage model is that it is not generalizable to future scenarios. Because price information is only related input, the traditional model cannot directly use production information and new load profiles, and should use a pricing technique to pre-process inputs.

2.4. Price-Based Market Model

Price production in the day-ahead market is studied in [44]. Among the various methods, the market simulation method irritates the market- clearing procedure by the market operator based on specific sales offers, load buy offers, and network parameters. Details of the market simulation model based on the low-level model are covered in the following equations. It is worth noting that in traditional storage modeling, the uncertainty of its price production strategies is not taken into account. Indeed, the pricing model that incorporates storage strategies is a two-level model [45]. The mentioned second and third issues address the challenges of the traditional storage arbitrage model in the production-based market simulation approach. First, future scenarios can be illustrated by generating new pricing information based on new production bid, load purchase bid, and network information. Second, the load distribution constraints of the lines can be constrained by equation 9, which is added to equations 3 to 8:

$$-LL_l \leq LF_{lt}^{in} + \sum_n GSF_{ln} * S_{it} \leq LU_l \quad i \in \Theta(n), \forall l, \forall t \qquad (9)$$

In the above equation, l is the bus symbol from 1 to N and LF^{in}_{lt} is the load distribution information of the solved lines with the market simulation model. LU and LL are high and low power constraints on the line 1, and GSF_{ln} is the power shift coefficient from n bus to line 1. S_i is also the output power of the storage system.

If there are multiple storage systems, the output of them will be correlated with the constraints of the lines. The market simulation model with similar production, load, and network information is used to generate price signals in the proposed two-level model.

2.5. Modeling the Two-level Arbitrage Storage system

Compared to the traditional model, the proposed two-level arbitrage storage method also incorporates marginal price information from the low-level market settlement procedure. Using good information such as wind forecasts, and estimated sales forecasts, the two-level approach can provide more accurate forecasts of marginal prices and more appropriate arbitrage estimates. In practice, a detailed model of the transmission network is used by the market independent operator to calculate prices per bus. When the storage arbitrage operations are present, this detailed model becomes complicated. In this paper, the linearized optimized load distribution method, i.e. DC load distribution, is used in the market clearing model to incorporate the storage effects on marginal prices in the network. Using the two-level formulation, the Arbitrage Storage Model and the Simulated Market Clearing Model become a two-level optimization problem. The high level is a matter of arbitrage from the point of view of the holder and the low level is the market clearing procedure. The two problems are related to each other with the LMP variable (π_{nt}) and the storage time (S_{it}). The optimization model is shown in equations 10 to 17.

$$Max\ R_y = \sum_t \sum_{i:[n\in\psi(i)]} \pi_{nt} S_{it} \tag{10}$$

The above equation seeks to maximize storage arbitrage revenue based on two factors: price and storage capacity. The above equation has some constraints, which include the constraints of equations 4 to 8.

In the low-level market-clearing model, the objective function 11 seeks to minimize productive payments in order to maximize social welfare for a fixed burden.

$$min \sum_t \sum_j c_{jt} G_{jt} \quad \forall \pi_{nt} \in \text{arg} \tag{11}$$

In the above equation c_{jt} is the proposed price of unit j and G_{jt} is the power output of unit j at time t in MW. Also, j represents the index of production units from 1 to j. In this respect, Arg or Argument means the range in which the price is defined.

Equation 12 guarantees the power balance between production and load.

$$\sum_j G_{jt} + \sum_i S_{it} = \sum_d D_{dt} - \sum_w P_{wt} : \lambda_t \quad , \forall t \tag{12}$$

In the above equation, G is the production of generators, S is the amount of storage power, D the load rate, which d is the index of loads from 1 to D, and P_{wt} is the produced power of the wind units and the w is the index of these units from 1 to W. λ also represents the Lagrangian coefficient of this relation.

Equation 13 also determines the load distribution constraints of the lines in which Θ (n) represents the components connected to the bus n.

$$\begin{aligned} -LL_l &\le LF_{lt} \\ &= \sum_n GSF_{ln}\left(G_{jt} + S_{it} + P_{wt} - D_{dt}\right) \\ &\le LU_l : \mu_{lt}^{min}, \mu_{lt}^{max}\ ,\ \{d,i,j,w\} \\ &\in \Theta(n), \forall l, \forall t \end{aligned} \tag{13}$$

In this equation, LF_{lt} is the line throughput, LU and LL are the high and low power constraints on the line 1, and GSF_{ln} is the power shift coefficient from bus n to line l, and the μ coefficients are related to the Lagrangian coefficients of this equation.

Equation 14 indicates the output constraints maximum and minimum of the production unit.

$$G_{jmin} \leq G_{jt} \leq G_{jmax}: \omega_{jt}^{min}, \omega_{jt}^{max}, \quad \forall j, \forall t \tag{14}$$

In the above relation G_{min} and G_{max} are the minimum and maximum product of j th generator and ω’s are Lagrangian coefficients.

Equation 15 indicates the slope rate constraints of production units.

$$RL_j \leq RG_{jt} = G_{jt} - G_{jt-1} \leq RU_j: \xi_{jt}^{min}, \xi_{jt}^{max}, \quad \forall j, \forall t \tag{15}$$

In the above equation, RL and RU denote the minimum and maximum slope rates of unit j and ξ is the Lagrangian coefficient assigned to this constraint.

Equation 16 also indicates Lagrange's low-level problem.

$$\begin{aligned} L_t = {} & \sum_j c_{jt} G_{jt} - \lambda_t * \left(\sum_j G_{jt} + \sum_i S_{it} = \sum_d D_{dt} - \sum_w P_{wt}\right) - \\ & \sum_l \mu_{lt}^{max} * (LU_l - LF_{lt}) - \\ & \sum_l \mu_{lt}^{min} * (LF_{lt} - LL_l) - \\ & \sum_l \omega_{jt}^{max} \left(G_{jmax} - G_{jt}\right) - \\ & \sum_l \omega_{jt}^{min} \left(G_{jt} - G_{jmin}\right) - \\ & \sum_l \xi_{jt}^{max} * (RU_j - RG_{jt}) - \\ & \sum_l \xi_{jt}^{min} * (RG_{jt} - RL_j) \end{aligned} \tag{16}$$

In equation 17, the marginal price π_{nt} is obtained from the partial derivative of equation 16 in terms of bus demand.

$$\pi_{nt} = \lambda_t + \sum_l GSF_{ln} (\mu_{jt}^{min} - \mu_{jt}^{max}) \quad \forall n, \forall t \tag{17}$$

It is worth noting that, the right part of the above equation are the dual variables associated with initial constraints.

The objective function of relation 11 minimizes production payments, assuming the demand is non-elastic. Equation 11 can be corrected for one inverse demand function and maximize social welfare without affecting the other constraints. There are details of maximizing social welfare with reference to the inverse demand function in [46]. The c_{jt} parameter in equation 11 is the cost of the estimated increase or proposed price of generator j at time t. This parameter can be obtained from the market information database [47].

The presence of internal-dependent variables between the upper and lower levels indicates the relationship between the two optimization problems. In other words, marginal prices in the high-level arbitrage problem are the results of the low-level market clearing problem, while low-level feeds and demand depend on the high-level storage schedule. Below we will discuss the details of the two-level problem.

2.6. Mathematical Program with Equilibrium Constraints (MPEC)

Considering the linearity of the market-clearing model based on DC optimal load distribution, the optimal solution of itis the single point that satisfies the KKT[1] optimality condition. In this case, the two-level arbitrage problem is formulated as a mathematical problem with equilibrium constraints, which is happened by applying low-level to high-level constraints using Kahn-Tucker terms as additional constraints. According to the dual theory, this MPEC model can be transformed into a hybrid

[1] Karush–Kuhn–Tucker

integer programming problem that can be easily solved through computational software. The MPEC formulation of the two-level arbitrage problem involves the high-level arbitrage model and the low-level Tucker condition. To complete the problem, the upper level is again expressed on the basis of equation 17 and with considering constraints 4 to 8.

$$maxR_y = \sum_t \sum_{i:[n\in\Psi(i)]} \pi_{nt} S_{it} \tag{18}$$

In the above equation, Ψ is a set of storage devices connected to bus i.

The Kahn-Tucker conditions for the low-level market clearing model include obtaining the primary variables (G_{it}, S_{it}) and dual variables (λ, μ, ω, ξ) that should satisfy the following equations:

$$c_{jt} = \lambda_t + \sum_l GSF_{ln}\left(\mu_{jt}^{min} - \mu_{jt}^{max}\right) + \omega_{jt}^{min} - \omega_{jt}^{max} \quad \forall j, n \in \psi \tag{19}$$

$$0 \le \mu_{lt}^{min} \perp LL_l + \sum_n GSF_{ln} * \left(G_{jt} + S_{it} + P_{wt} - D_{dt}\right) \ge 0 \tag{20}$$

$$0 \le \mu_{lt}^{max} \perp LU_l - \sum_n GSF_{ln} * \left(G_{jt} + S_{it} + P_{wt} - D_{dt}\right) \ge 0 \tag{21}$$

$$0 \le \omega_{jt}^{min} \perp G_{jt} - G_{jmin} \ge 0 \tag{22}$$

$$0 \le \omega_{jt}^{max} \perp G_{jmax} - G_j \ge 0 \tag{23}$$

$$0 \le \xi_{jt+1}^{min} \perp G_{jt+1} - G_{jt} \ge 0 \tag{24}$$

$$0 \le \xi_{jt+1}^{max} \perp RU_j - G_{jt+1} + G_{jt} \ge 0 \tag{25}$$

In the above equations {d, i, j, w} are members of Θ (n). Also, in the above relationships, symbol ⊥ represents the external multiplication of the corresponding variables in the vector form.

2.7. Mixed Integer Linear Programming (MILP)

The MILP technique is used to reformulate the MPEC nonlinear problem, which is generated in [48] at the optimal point by reference to the nonlinear expression in terms of the linear combination of variables and using the dual theory that leads to the MILP formulation given in the following equations:

$$\begin{aligned} maxR_y &= \sum_t \lambda_t * \sum_d D_{dt} + \sum_l \mu_{lt}^{\prime max} * [-LU_l - \sum_{n:\{d,\omega\}\in\psi(n)} GSF_{ln} * (-P_{wt} + D_{dt})] + \mu_{lt}^{\prime min} * [-LL_l + \sum_{n:\{d,\omega\}\in\psi(n)} GSF_{ln} * (-P_{wt} + D_{dt})] \\ &+ \sum_j [\omega_{jt}^{max}\left(-G_{jmax}\right) + \omega_{jt}^{min}\left(G_{jmin}\right)] + \sum_j [\xi_{jt}^{max}\left(-RU_j\right) + \xi_{jt}^{min}\left(RL_j\right)] - \sum_j c_{jt} * G_{jt} \end{aligned} \tag{26}$$

The above equation has the constraints of the equations 4 to 8 as well as the constraints of 9 and the following constraints:

$$0 \leq \mu_{lt}^{min} \leq M_{\mu}^{min} v_{\mu lt}^{min} \quad (27)$$

$$0 \leq \mu_{lt}^{max} \leq M_{\mu}^{max} v_{\mu lt}^{max} \quad (28)$$

$$0 \leq LL_l + \sum_n GSF_{ln} * \left(G_{jt} + S_{it} + P_{wt} + D_{dt}\right) \leq M_{\mu}^{min}(1 - v_{\mu lt}^{min}) \quad (29)$$

$$0 \leq LU_l + \sum_n GSF_{ln} * \left(G_{jt} + S_{it} + P_{wt} + D_{dt}\right) \leq M_{\mu}^{max}(1 - v_{\mu lt}^{max}) \quad (30)$$

$$0 \leq \omega_{jt}^{min} \leq M_{\omega}^{min} v_{\omega jt}^{min} \quad (31)$$

$$0 \leq \omega_{jt}^{max} \leq M_{\omega}^{max} v_{\mu jt}^{max} \quad (32)$$

$$0 \leq G_{jt} - G_{jmin} \leq M_{\omega}^{min}(1 - v_{\omega jt}^{min}) \quad (33)$$

$$0 \leq G_{jmax} - G_{jt} \leq M_{\omega}^{max}(1 - v_{\omega jt}^{max}) \quad (34)$$

$$0 \leq \xi_{jt}^{min} \leq M_{\xi}^{min} v_{\xi jt}^{min} \quad (35)$$

$$0 \leq \xi_{jt}^{max} \leq M_{\xi}^{max} v_{\xi jt}^{max} \quad (36)$$

$$0 \leq G_{jt} - G_{jt-1} - RL_j \leq M_{\xi}^{min}(1 - v_{\xi jt}^{min}) \quad (37)$$

$$0 \leq RU_j - G_{jt} + G_{jt-1} \leq M_{\xi}^{max}(1 - v_{\xi jt}^{max}) \quad (38)$$

In the above equations $M^{min}{}_{\mu}$ and $M^{max}{}_{\mu}$, $M^{min}{}_{\omega}$ and $M^{max}{}_{\omega}$, $M^{min}{}_{\xi}$ and $M^{max}{}_{\xi}$ are large constants and $v^{min}{}_{\mu}$ and $v^{max}{}_{\mu}$, $v^{min}{}_{\omega}$ and $v^{max}{}_{\omega}$, $v^{min}{}_{\xi}$ and $v^{max}{}_{\xi}$ are additional binary variables [45].

In the formulated model, there are two additional binary variables (upper and lower bounds) for each transmission line, generator output and generator slope constraint. In addition, each storage system has two binary variables to display the charge and discharge. Continuous variables include storage and discharge power, generator's outputs, and local marginal prices. In addition, dual variables equal to the number of constraints of the original problem, are also continuous. An additional constraint can be added for binary variables to improve computational performance as follows:

$$v_{\tau lt}^{min} + v_{\tau lt}^{max} \leq 1 \qquad \forall l, \forall t, \tau \in \{\mu, \omega, \xi\} \quad (39)$$

Large values of constant M must be adjusted appropriately to connect the main and dual variables. Large M-constants must be modified by their corresponding constraints and selected on the basis of the known parameters of those constraints. For instance, the high constraints on production, $M^{max}{}_{\omega}$ is inserted equal to two to three times the maximum constraint on all generators. For dual price variables, the large M-constants are empirically considered large enough. This study considers $M^{min}{}_{\mu}$ and $M^{min}{}_{\mu}$ values of 1000 to yield feasible solutions. The particle swarm method is used to optimize the problem.

2.8. Time Horizon for Evaluating Storage Arbitrage

The problem of estimating annual arbitrage potential over a year is defined as 8760 hourly intervals. Solving the whole problem offers many variables and constraints that are computationally impractical. Therefore, the problem is divided annually into sub-problems with a smaller time horizon. The length of the time horizon for each problem should be determined. The storage system that runs Arbitrage is present in a day-ahead market and its annual income is calculated by adding up the possible daily results. This method can reduce the range of storage operation and result in a small time horizon. The charging status of the storage system is a variable that connects the operation between successive time intervals. In the revenue maximization objective function, the SOC at the end of the simulation horizon is limited to the same level as the beginning of the interval. Otherwise, the repository must be recharged as far as possible to achieve the intended purpose. With such a constraint for the 24-hour time horizon, the storage capacity of the storage system is less than optimal and the solution may be incorrect to reflect the true arbitrage potential.

This paper uses a weekly evaluation time horizon for each sub-problem that can be resolved quickly and storage capacities can be utilized better. [49] indicates that the storage system achieves more financial and technical benefits in weekly scheduling than daily one.

2.9. Uncertainty Modeling

With a high level of infiltration, wind power fluctuations affect marginal price changes in the system for storage arbitrage. The wind power prediction model consists of two parts: a point-based time-series method and a probabilistic error-based probability distribution. Prediction scenarios can be obtained by adding samples of the prediction error distribution to the time series point forecasts. The GARCH time series model for point prediction and beta distribution prediction error model are discussed below. Wind power output has a significant impact on storage arbitrage, which is influenced by power fluctuations affecting the margin price of the day ahead. Time series prediction methods can represent the trend of variables compared to probabilistic distribution methods. In this paper, wind power point prediction is obtained through the GARCH model, which can take into account the effects of deviations. This method is taken from [50]. After forecasting, for each wind farm, wind information is scaled based on the nominal power throughout the year. The Gaussian distribution is appropriate for the wind forecast error. A more accurate model for predicting the most appropriate beta distribution model is predicted based on wind velocity because the prediction error is distributed unevenly for different wind levels [51]. The main idea of this method is to create a probability distribution function of the forecast error for each power forecasting range. Multiple historical information from metrics and forecast information is used to create a model and fit the beta distribution.

The model details are as follows. In the first step, the normalized wind power prediction errors, ie $e_d = (p_a - p_f) / p_{rated}$, are calculated in the range [-1,1]. In the second step, a linear mapping function, $e = (e_d + 1) / 2$, is selected for mapping the error to the interval [0,1] so that the beta distribution defined in the interval [0,1] can be used. In step 3, ten equal prediction sets are selected from 0 to 1 and the prediction errors e are attributed to each of the ranges. When prediction range-based distributions are used to generate wind scenario information, prediction errors are sampled from distributions and mapped to [-1,1] before converting to nominal values.

3. SIMULATION RESULTS

3.1. Introducing Test Grid

To evaluate the performance of the proposed two-level method, this model is implemented on the IEEE 118-bus test system. The system has 118 bus, 54 generators, 186 lines and 5000 MW load and 9966 MW capacity of production. Production information is taken from [52]. Fig.2 illustrates a single-line diagram of the test system. They offer 20 low-cost generators with $ 5, 5.5 and $ 0.5 to $ 11 to $ 19.5. There are 20 expensive generators in the range of $ 30 to $ 49 with a 1dollar increase. Finally, there are 14 very expensive generators with bids of $ 70 to $ 83 at a rate of $ 1. There are seven thermal lines on transmission lines that are 100 MW for lines 1-3 and 6-7, 175 MW for lines 3-12 and 46-47, 150 MW for line 15-33 and 300 MW for line 71-72 and 250 MW for the line 70-75. Five wind farms have been added to buses 8, 28, 48, 68 and 88 with a nominal power of 200 MW. The beta probability

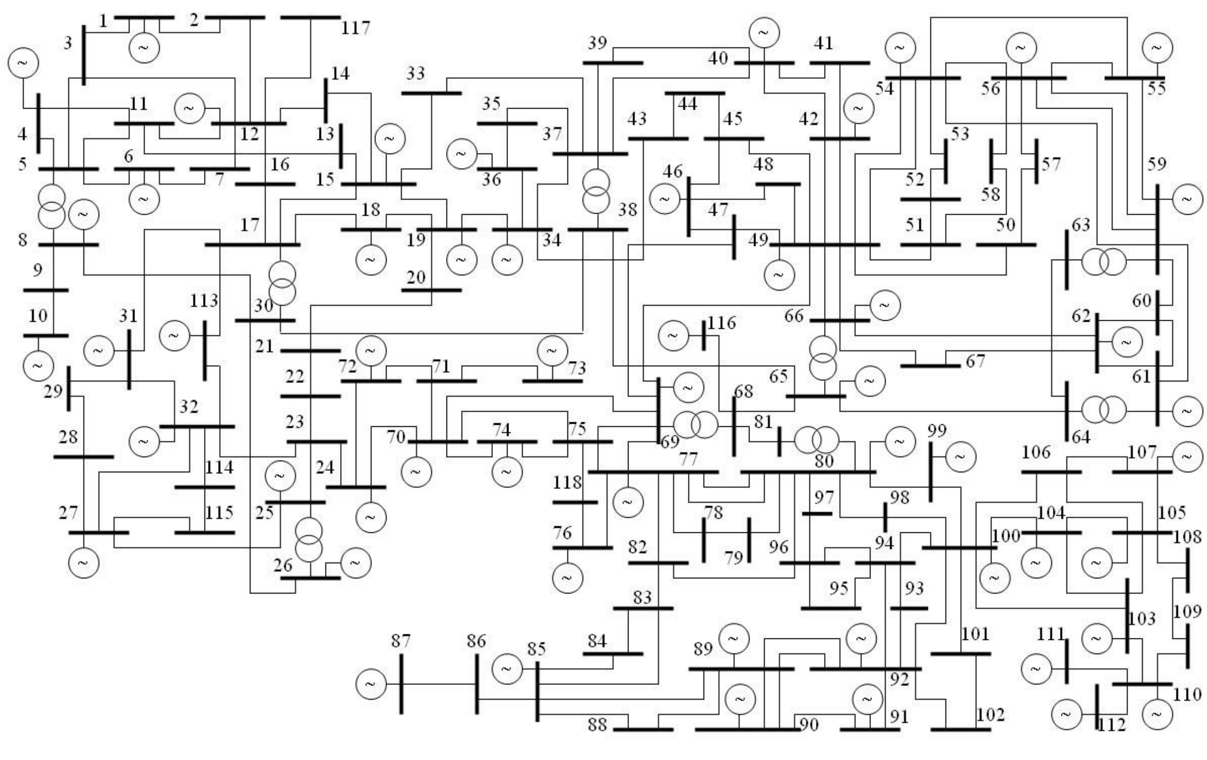

Fig. 2. IEEE 118 bus test network diagram [49].

distribution function for the ten wind forecast sets is based on [53-54]. The prediction errors change with the predicted power. The closer the prediction power is to zero or the maximum, the more likely the prediction errors become. Power point prediction is performed with 80% assurance interval and GARCH time series method for predicting wind power and modeling error based prediction set for arbitrage model data preparation. From the error distributions, five samples are added to the point prediction to obtain five wind scenarios. The two storage systems are rated at 100 MW and 2000 MW at 33 and 15 buses, with the most marginal price changes. From the error distributions, five samples are added to the point prediction to obtain five wind scenarios. Two storage systems are installed at 100 MWH and 2000 MWH at 15 and 33 buses, with the most marginal price changes.

3.2. Analysis of Results

In this section, we discuss the results of the proposed two-level method in the 118-bus test network. Fig. 3 displays the load profile on bus 33 that is under discussion. In the IEEE 118 bus test network, the system has sufficient production capacity and transmission density is adequate. Fig. 4 illustrates the marginal price of bus 33 and Fig. 5 demonstrates the power of the storage system, Fig. 6 shows the charging status of the storage system. In these figures, the proposed method is compared with the traditional method. From Figures 3 to 6, we can see the effect of the presence of storage system 1 on bus 33. It can be seen from Fig. 4 that the two-level model can clearly soften the marginal price by lowering the price at peak times and raising at non-peak times. In Fig. 5, where the power output of the storage

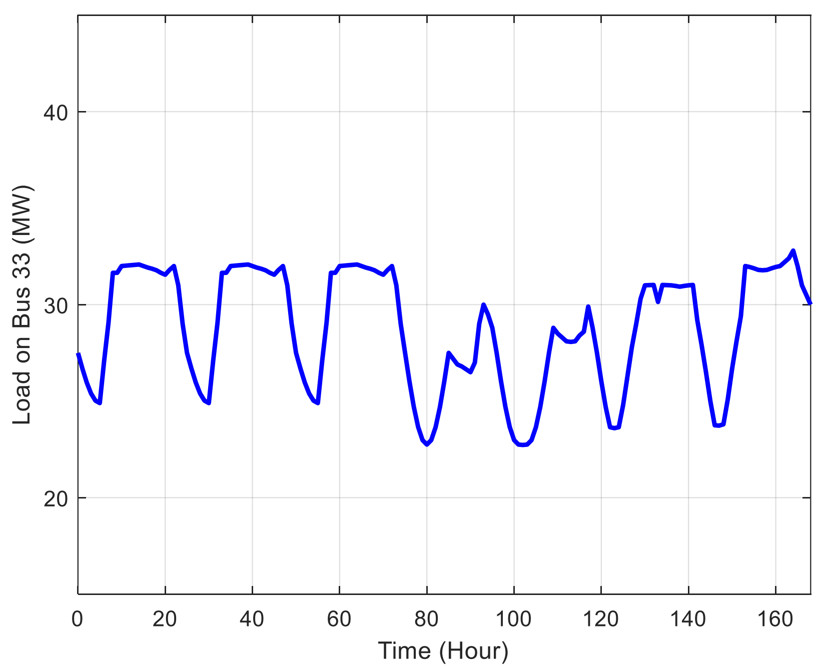

Fig. 3 The amount of load on the test grid on bus 33 of the storage location.

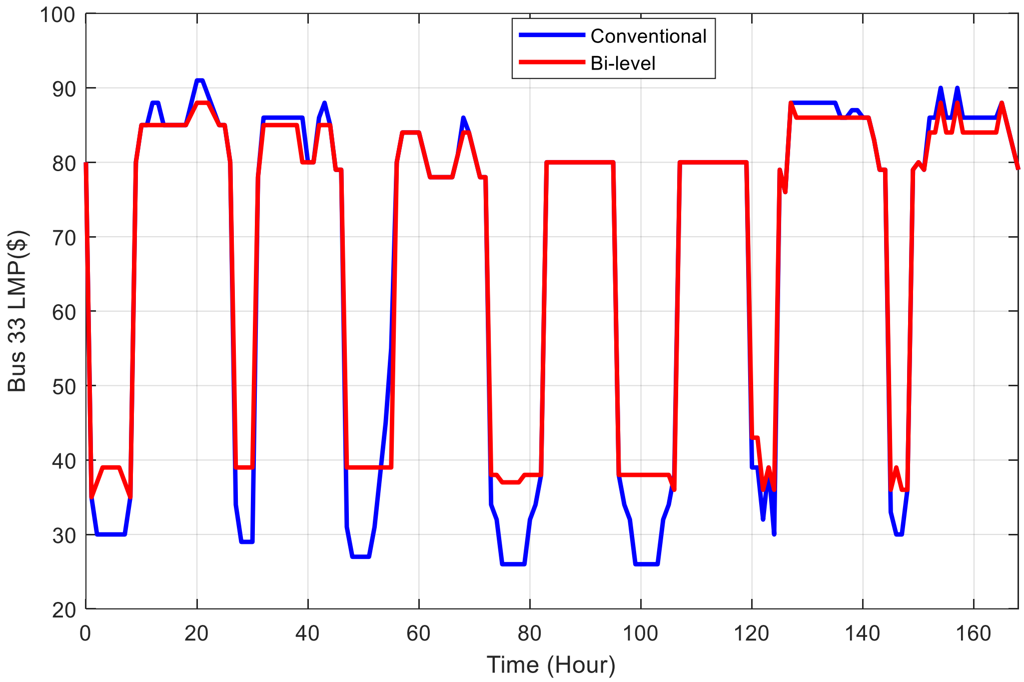

Fig. 4. Comparison of marginal price value in bus 33.

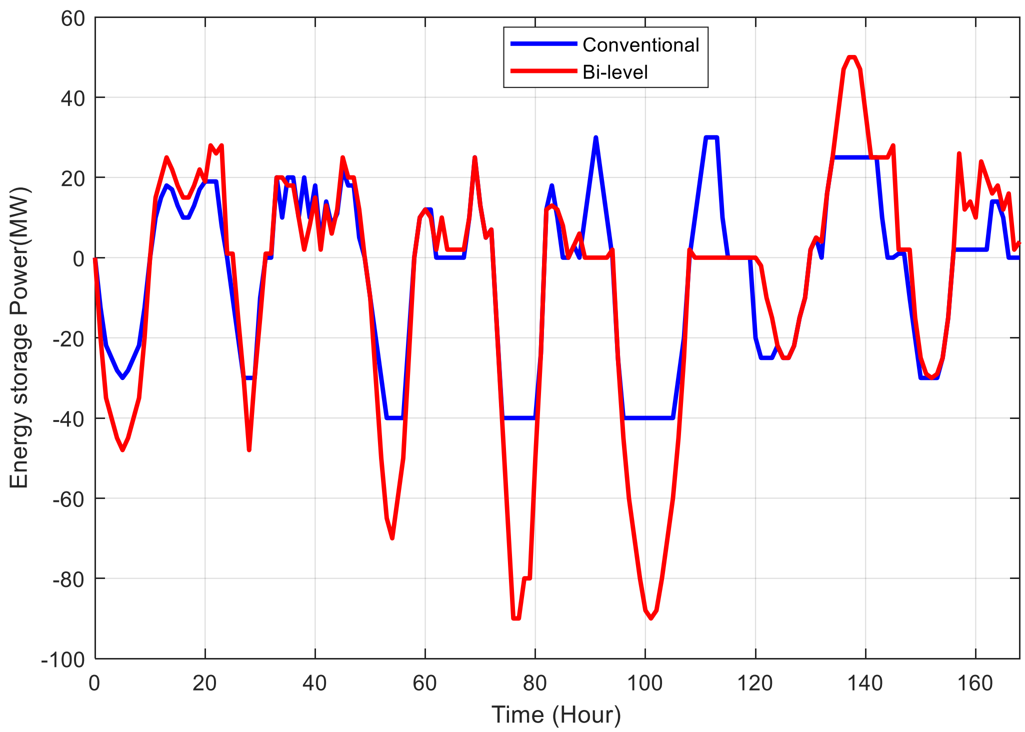

Fig. 5. Comparison of output power of storage 1 in both traditional and two-level methods.

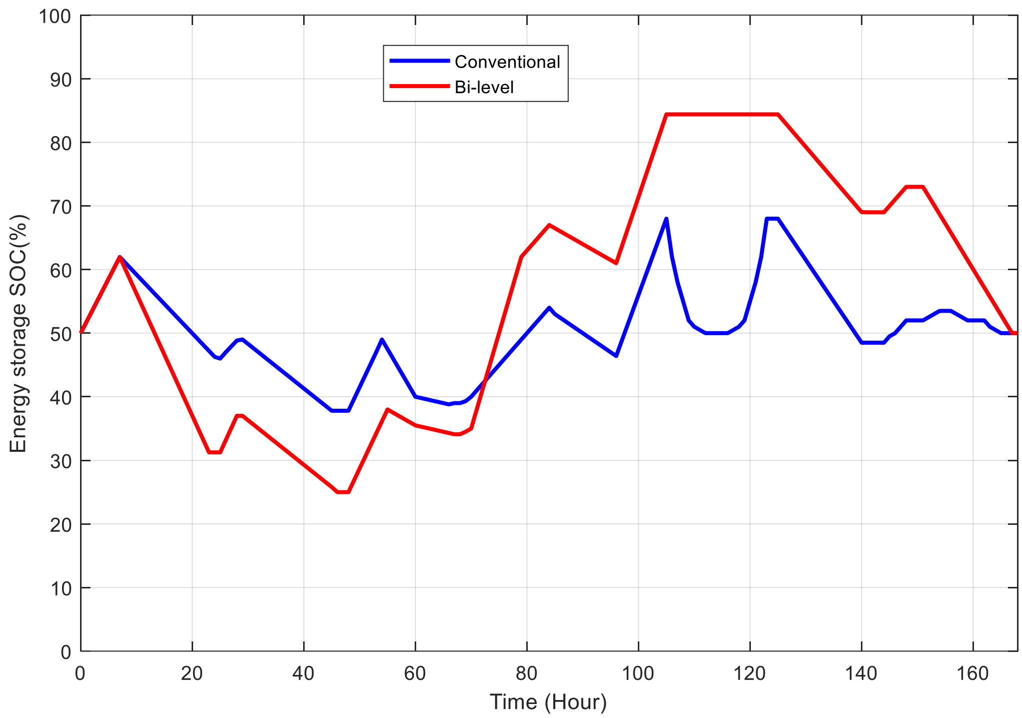

Fig. 6. Comparison of storage 1's charging state on both traditional and two-level models.

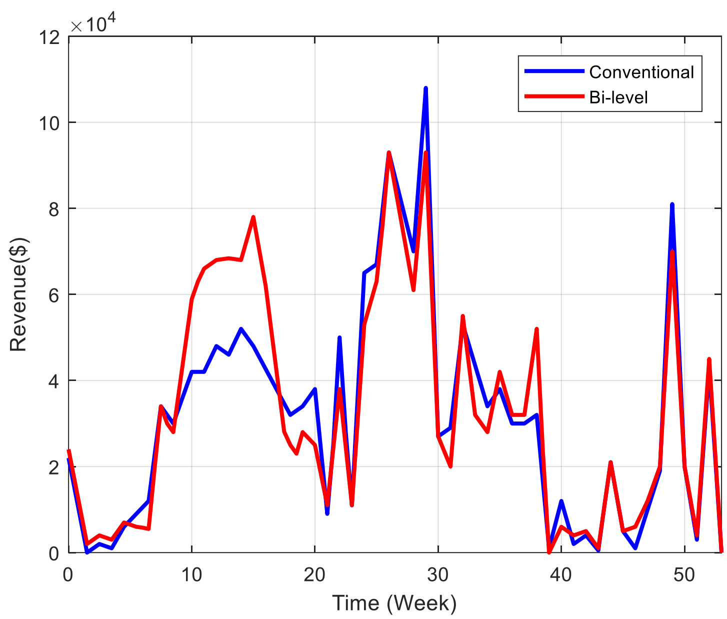

Fig. 7. Weekly Arbitrage Income on the IEEE 118 Bus Test Network.

system is shown, it can be seen that the storage's charging power of the traditional model is much lower than that of the two-level model at low marginal hours. Although the marginal price in the two-level model increases during the charging process, it is still lower than the marginal price when the power storage later sells energy. The traditional method of the storage system is not able to store enough energy at times of low marginal cost, which results in low profit.

The annual arbitrage values using the price information generated for the traditional and two-level models are $ 1.67 million and $ 1.71 million, respectively. It is worth noting that the traditional model has less revenue. Fig. 7 also shows weekly arbitrage income, with the two-level model, clearly earning more in the 10 to 16 weeks. Consider Week 11, for example, where the revenue from traditional and two-level models is $ 43280 and $ 65700, respectively.

Below we discuss the density of the lines. Analyzing the results, it can be seen that line 15-33 is always at its full capacity of 150 MW. The GSF shift factor of buses 33 and 15 to this line is -0.46 and -0.13, respectively. This means that the two storage systems have to work in the opposite direction in terms of the storage's output power. For every 0.13 MW absorbed in storage 1, there must be 0.46 MW output on storage 2 to meet the line constraint. This is illustrated in Fig. 8.

If only one storage system is installed on bus 33, the storage system will, in no way, be able to charge due to the congestion on line 15-33 and the arbitrage revenue will decrease. In the two-level model constraint, the lines are dynamically optimized based on the product proposition and the storage arbitrage. Because the storage system contributes to the market-clearing in the low-level model, the outputs of the generators in

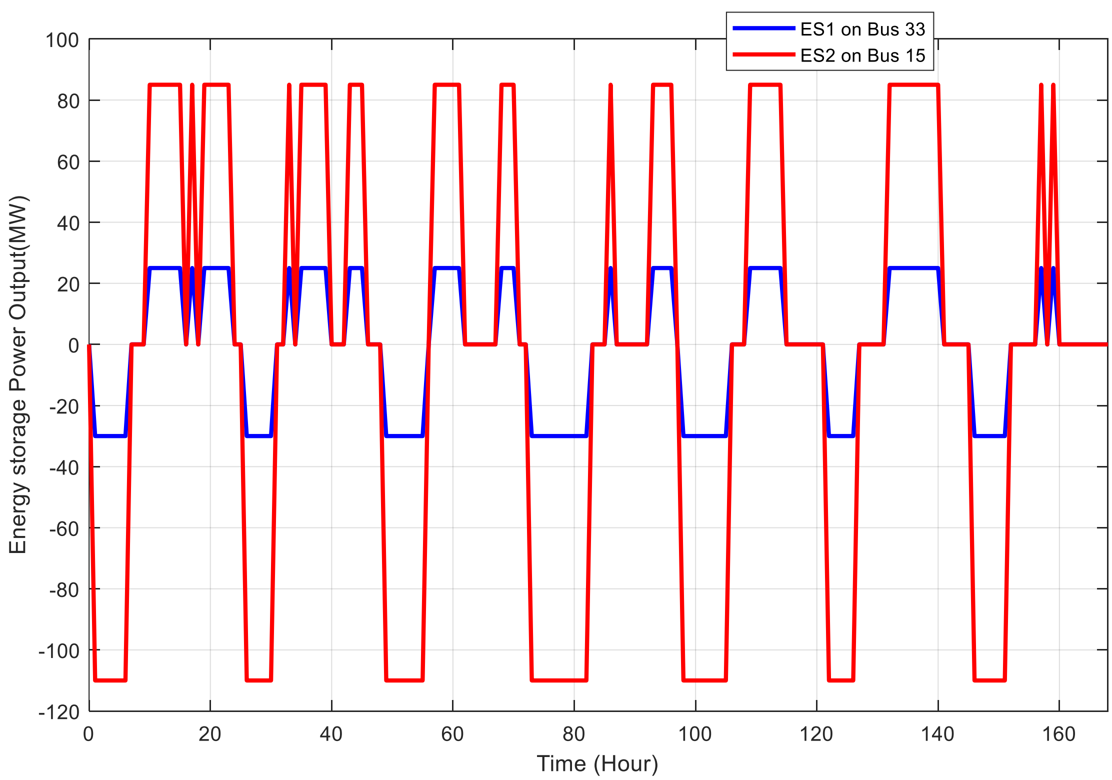

Fig. 8. Storage output with line constraints.

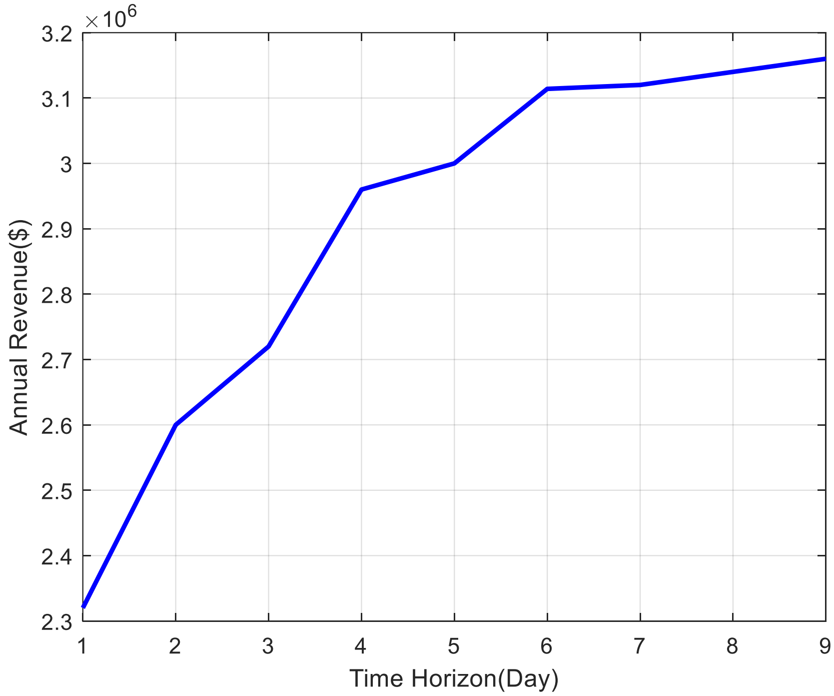

Fig. 9. Time horizon effect on arbitrage income.

the pricing scenarios are different with and without the storage. With bids, the storage system is able to exploit the greater capacity of the transmission lines at higher prices. This partnership will dramatically increase revenue. Finally, Fig. 9 demonstrates the effect of the time horizon on arbitrage income. In this form, the various ranges of the time horizon from day to month are discussed. The time horizon of 365 days has not been investigated due to the large test network. The first observation is that the time horizon of a very bad day is in estimating income. As the time horizon increases, arbitrage income is narrowed due to initial and final SOC constraints and storage capacity is exploited more appropriately. The time horizon, of course, must also be considered on the basis of computational complexity.

4. CONCLUSION

In this paper, the issue of maximizing the arbitrage revenue of storage units in power systems in the presence of wind resources was also discussed. Storage Arbitrage's proposed two-level approach included the information of marginal pricing from the market clearing procedure on the low-level problem. The proposed method achieves more accurate forecasts of marginal prices and more appropriate estimates of arbitrage using appropriate information such as wind forecasts and estimated production sales offers. A detailed model of the transmission network is used by the market independent operator to calculate prices per bus. When the storage arbitrage operations are present, this detailed model becomes complicated. In this paper, the linearized optimized load distribution method, ie DC load distribution, is used in the market-clearing model to incorporate the effects of the storage system on marginal prices on the network. Using the two-level formulation, the Arbitrage Storage Model and the Simulated Market-Clearing Model become a two-level optimization problem. The high level is a matter of arbitrage from the point of view of the storekeeper and the low level is the market-clearing procedure. In the proposed method, the conversion technique was used for single-line programming considering the system equilibrium constraints. The proposed method was implemented on the IEEE 118 bus test network, and the results revealed that the proposed method was significantly better than the traditional method and achieved higher arbitrage revenue. The two-level model has clearly softened the marginal price by lowering the price at peak times and raising at non-peak times. traditionally, the storekeeper is not able to store enough energy at times of low marginal cost, resulting in a low profit. With market-offerings, the storekeeper has exploited the greater capacity of transmission lines at higher prices, and this partnership significantly increases revenue. The results show that the proposed algorithms can increase energy storage revenue from traditional to two-level models from $ 43280 to $ 65700, respectively.

REFERENCES

[1] P. D. Lund, J. Lindgren, J. Mikkola, and J. Salpakari, "Review of energy system flexibility measures to enable high levels of variable renewable electricity," Renewable and Sustainable Energy Reviews, vol. 45, pp. 785-807, 2015.

[2] A. S. Brouwer, M. van den Broek, A. Seebregts, and A. Faaij, "Impacts of large-scale Intermittent Renewable Energy Sources on electricity systems, and how these can be modeled," Renewable and Sustainable Energy Reviews, vol. 33, pp. 443-466, 2014.

[3] A. Palzer and H.-M. Henning, "A comprehensive model for the German electricity and heat sector in a future energy system with a dominant contribution from renewable energy technologies – Part II: Results," Renewable and Sustainable Energy Reviews, vol. 30, pp. 1019-1034, 2014.

[4] D. Arent, J. Pless, T. Mai, R. Wiser, M. Hand, S. Baldwin, et al. ,"Implications of high renewable electricity penetration in the U.S. for water use, greenhouse gas emissions, land-use, and materials supply," Applied Energy, vol. 123, pp. 368-377, 2014.

[5] S. Weitemeyer, D. Kleinhans, T. Vogt, and C. Agert, "Integration of Renewable Energy Sources in future power systems: The role of storage," Renewable Energy, vol. 75, pp. 14-20, 2015.

[6] M. F. Romlie, M. Rashed, C. Klumpner, and G. M. Asher, "An Analysis of Efficiency Improvement with the Installation of Energy Storage in Power Systems," IET Conference Proceedings, vol. 112, pp. 355-379, 2014.

[7] M. Z. Daud, A. Mohamed, and M. Hannan, "An improved control method of battery energy storage system for hourly dispatch of photovoltaic power sources," Energy Conversion and

Management, vol. 73, pp. 256-270, 2013.

[8] S. Teleke, M. E. Baran, S. Bhattacharya, and A. Q. Huang, “Rule-based control of battery energy storage for dispatching intermittent renewable sources,” Sustainable Energy, IEEE Transactions on, vol. 1, pp. 117-124, 2010.

[9] S. Koohi-Kamali, V. Tyagi, N. Rahim, N. Panwar, and H. Mokhlis, “Emergence of energy storage technologies as the solution for reliable operation of smart power systems: a review,” Renewable and Sustainable Energy Reviews, vol. 25, pp. 135-165, 2013.

[10] N. S. Hasan, M. Y. Hassan, M. S. Majid, and H. A. Rahman, “Review of storage schemes for wind energy systems,” Renewable and Sustainable Energy Reviews, vol. 21, pp. 237-247, 2013.

[11] J. P. Deane, B. Ó. Gallachóir, and E. McKeogh, “Techno-economic review of existing and new pumped hydro energy storage plant,” Renewable and Sustainable Energy Reviews, vol. 14, pp. 1293- 1302, 2010.

[12] D. Burnett, E. Barbour, and G. P. Harrison, “The UK solar energy resource and the impact of climate change,” Renewable Energy, vol. 71, pp. 333-343, 2014.

[13] S. Vazquez, S. M. Lukic, E. Galvan, L. G. Franquelo, and J. M. Carrasco, “Energy storage systems for transport and grid applications,” Industrial Electronics, IEEE Transactions on, vol. 57, pp. 3881-3895, 2010.

[14] M. Milligan, P. Donohoo, D. Lew, E. Ela, B. Kirby, H. Holttinen, et al. “Operating reserves and wind power integration: an international comparison,” in proc. 9th International Workshop on large-scale integration of wind power into power systems vol. 3, pp. 18-29, 2010.

[15] J. P. Barton and D. G. Infield, “A probabilistic method for calculating the usefulness of a store with finite energy capacity for smoothing electricity generation from wind and solar power,” Journal of power sources, vol. 162, pp. 943-948, 2006.

[16] Oytun Babacan, William Torre, Jan Kleissl, “Siting and sizing of distributed energy storage to mitigate voltage impact by solar PV in distribution systems,” Solar energy, Vol. 146, pp 199-208, 2017.

[17] A. S. Awad, J. D. Fuller, T. H. M. El-Fouly, and M. M. Salama, “Impact of energy storage systems on electricity market equilibrium,” IEEE Trans. Sustain. Energy, vol. 5, no. 3, pp. 875–885, Jul. 2014.

[18] Yang Zhang, Pietro Elia Campana, Anders Lundblad, Jinyue Yan, “Comparative study of hydrogen storage and battery storage in grid connected photovoltaic system: Storage sizing and rule-based operation,”Applied energy, Vol. 201,pp. 397-411, 2017.

[19] W. F. Su, C. E. Lin, and S. J. Huang, “Economic analysis for demandside hybrid photovoltaic and battery energy storage system,” in Proc. Ind. Appl.

Conf. 34th IAS Annual Meeting, vol. 3, pp. 2051–205, 1999.

[20] Bahman Bahmani-Firouzi, Rasoul Azizipanah-Abarghooee, "Optimal sizing of battery energy storage for micro-grid operation management using a new improved bat algorithm," Electrical Power and Energy Systems, Vol. 192, pp. 268-280, 2014.

[21] Bananeh Ansari, Di Shi, Ratnesh Sharma, and Marcelo G. Simoes, "Economic analysis, optimal sizing and management of energy storage for PV grid integration," ransmission and Distribution Conference and Exposition (T&D), IEEE/PES, Vol. 118, pp. 110-121, 2016.

[22] Pavithra Harsha, Munther Dahleh, "Optimal Management and Sizing of Energy Storage under Dynamic Pricing for the Efficient Integration of Renewable Energy," IEEE Transactions on Power Systems, pp. 81-94, december 2013.

[23] Kyri Baker, Gabriela Hug, Senior, and Xin Li, Senior, "Energy Storage Sizing Taking into Account Forecast Uncertainties and Receding Horizon Operation," IEEE Transactions on Sustainable Energy, Vol. 118, pp. 246-258, 2016.

[24] Hamed Valizadeh Haghi, and Saeed Lotfifard, "Spatiotemporal Modeling of Wind Generation for Optimal Energy Storage Sizing,"IEEE Transactions on Sustainable Energy, Vol. 9,pp. 142-153, january 2015 .

[25] Xiangqi Zhu, Jiahong Yan, and Ning Lu, "A Probabilistic-based PV and Energy Storage Sizing Tool for Residential Loads," Transmission and Distribution Conference and Exposition (T&D), IEEE/PES, Vol. 118, pp. 110-121, 2016.

[26] M Kintner-Meyer, P Balducci, W Colella, M Elizondo, C Jin, T Nguyen, V Viswanathan, Y Zhang, National Assessment of Energy Storage for Grid Balancing and Arbitrage: Phase 1, WECJune 2012.

[27] Y. Yun Xie, W. Guo, "Robust MPC-based bidding strategy for wind storage systems in real-time energy and regulation markets", International Journal of Electrical Power & Energy Systems, Vol. 124, 106361, 2021.

[28] K. DasAnatole, L. Theodore, Ph. Grapperon, P. E.Sørensen, A. D.Hansen, "Optimal battery operation for revenue maximization of wind-storage hybrid power plant", Electric Power Systems Research, Vol. 189, 106631, 2020.

[29] M. A. Lasemi, A. Arabkoohsar, "Optimal operating strategy of high-temperature heat and power storage system coupled with a wind farm in energy market", Energy, Vol. 210, 118545, 2020.

[30] M. Bilal, J. Thakur, "Assessment of curtailed wind energy potential for off-grid applications through mobile battery storage", Energy, Vol. 201, 117601,2020.

[31] Hao Wang, Baosen Zhang, "Energy Storage Arbitrage in Real-Time Markets via Reinforcement Learning", Systems and Control journal, cornel university, 2018

[32] Md Umar Hashmi, Arpan Mukhopadhyay, Ana Bušić, Jocelyne Elias, "Optimal Storage Arbitrage under Net Metering using Linear Programming", Electrical Engineering and Systems Science journal, 2019.

[33] Raymond H. Byrne, Tu A. Nguyen, David A. Copp, "Opportunities for Energy Storage in CAISO: Day-Ahead and Real-Time Market Arbitrage", International Symposium on Power Electronics, 2018.

[34] Alireza Akbari-Dibavar, Kazem Zare, Sayyad, "hybrid stochastic-robust optimization approach for energy storage arbitrage in day-ahead and real-time markets". Sustainable Cities and Society, 2019.

[35] Md Umar Hashmi; Wael Labidi; Ana Bušić; Salah-Eddine Elayoubi, "Long-Term Revenue Estimation for Battery Performing Arbitrage and Ancillary Services",2018 IEEE International Conference on Communications, Control, and Computing Technologies for Smart Grids (SmartGridComm), 2018.

[36] Tom Terlouwa, Tarek AlSkaifa, Christian Bauer, Wilfried van Sark, Multi-objective optimization of energy arbitrage in community energy storage systems using different battery technologies", Applied energy, 2019.

[37] Xin Fang; Bri-Mathias Hodge; Linquan Bai; Hantao Cui; Fangxing Li, "Mean-Variance Optimization-Based Energy Storage Scheduling Considering Day-Ahead and Real-Time LMP Uncertainties", IEEE Transactions on Power Systems, 2018.

[38] R. H. Byrne and C. A. Silva-Monroy, “Estimating the maximum potential revenue for grid connected electricity storage: Arbitrage and regulation,” SandiaNatl. Labs,Albuquerque,NM, USA, Tech. Rep. SAND2012-3863, Dec. 2012.

[39] K. Bradbury, L. Pratson, and D. Pati˜no-Echeverri, “Economic viability of energy storage systems based on price arbitrage potential in real-time U.S. electricity markets,” Appl. Energy, vol. 114, pp. 512–519, 2014.

[40] R. Walawalkar, J. Apt, and R. Mancini, “Economics of electric energy storage for energy arbitrage and regulation in New York,” Energy Policy, vol. 35, pp. 2558–2568, 2007.

[41] M. Ghofrani, A. Arabali, M. Etezadi-Amoli, and M. S. Fadali, “A framework for optimal placement of energy storage units within a power system with high wind penetration,” IEEE Trans. Sustain. Energy, vol. 4, no. 2, pp. 434–442, Apr. 2013.

[42] Electric Storage Participation inMarkets Operated by Regional Transmission Organizations and Independent System Operators, 157 FERC 61,121 (2016) (Docket Nos. RM16-23-000 & AD16-20-000).

[43] H. Chen, T. N. Cong, W. Yang, C. Tan, Y. Li, and Y. Ding, “Progress in electrical energy storage system: A critical review,” Prog. Nat. Sci., vol. 19, no. 3, pp. 291–312, 2009.

[44] D. Krishnamurthy, C. Uckun, Z. Zhou, P. Thimmapuram, and A. Botterud, “Energy storage arbitrage under day-ahead and real-time price uncertainty,”

IEEE Trans. Power Syst., vol. PP, no. 99, p. 1, doi: 10.1109/TPWRS.2017.2685347.

[45] X. Fang, Y. Wei, and F. Li, “Evaluation of LMP intervals considering wind uncertainty,” IEEE Trans. Power Syst., vol. 31, no. 3, pp. 2495–2496, May 2016.

[46] C. Ruiz and A. J. J. Conejo, “Pool strategy of a producer with endogenous formation of locationalmarginal prices,” IEEE Trans. Power Syst., vol. 24, no. 4, pp. 1855–1866, Nov. 2009.

[47] J. Yang, F. Li, and L. Freeman, “A market simulation program for the standard market design and generation/transmission planning,” in Proc. IEEE PES Gen. Meeting, 2003, pp. 442–446.

[48] J. Fortuny-Amat and B. McCarl, “A representation and economic interpretation of a two-level programming problem,” J. Oper. Res. Soc., vol. 32, no. 9, pp. 783–792, 1981.

[49] H. Khani and M. R. D. Zadeh, “Real-time optimal dispatch and economic viability of cryogenic energy storage exploiting arbitrage opportunities in an electricity market,” IEEE Trans. Smart Grid, vol. 6, no. 1, pp. 391–401, Jan. 2015.

[50] H. Chen, Q. Wan, F. Li, and Y. Wang, “GARCH in mean type models for wind power forecasting,” IEEE Power Energy Soc. Gen. Meeting, Vancouver, BC, Canada, 2013, pp. 1–5. doi: 10.1109/PESMG.2013.6672237.

[51] H. Bludszuweit, J. A. Dominiguez-Navarro, A. Llombart, and J. A. Dominguez-Navarro, “Statistical analysis of wind power forecast error,” IEEE Trans. Power Syst., vol. 23, no. 3, pp. 983–991, Aug. 2008.

[52] X. Fang, Q. Hu, F. Li, B. Wang, and Y. Li, “Coupon-based demand response considering wind power uncertainty: A strategic bidding model for load serving entities,” IEEE Trans. Power Syst., vol. 31, no. 2, pp. 1025– 1037, Mar. 2015.

[53] Hantao Cui, Student Member, IEEE, Fangxing Li, Fellow, IEEE, Xin Fang, "Bilevel Arbitrage Potential Evaluation for Grid-Scale Energy Storage Considering Wind Power and LMP Smoothing Effect"IEEE TRANSACTIONS ON SUSTAINABLE ENERGY, VOL. 9, NO. 2, APRIL 2018.

[54] Xin Fang, Student Member, IEEE, Qinran Hu, Student Member, IEEE, Fangxing Li, Senior Member, IEEE, Beibei Wang, Member, IEEE, and Yang Li, Member, IEEE , "Coupon-Based Demand Response Considering Wind Power Uncertainty: A Strategic Bidding Model for Load Serving Entities", IEEE TRANSACTIONS ON POWER SYSTEMS, 2015.