Optimal selection and sizing of hybrid energy storage systems for wind power dispatching

MARZIEH KHOSRAVI[1], SAEED AFSHARNIA[1,*], AND SHAHROKH FARHANGI[1]

[1]School of Electrical and Computer Engineering, College of Engineering, University of Tehran, North Kargar st., Tehran, Iran, Postal Code: 1439957131
[*]Corresponding author: Saeed Afsharnia

Manuscript received 08 December, 2020; revised 18 February, 2021; accepted 18 February, 2021. Paper no. JEMT-2012-1268.

Wind power uncertainty is one of the problems in large-scale wind farms integration to the network. The use of Energy Storage Systems (ESSs) is a practical solution to enhance availability and power dispatching possibility of renewable energy sources (RESs). RESs need an ESS with high power and energy capacity while none of ESSs has this feature at the same time. The accepted solution for this problem is using the hybrid energy storage system (HESS). In this paper, HESS optimal sizing and power dispatching of wind-HESS system are considered, simultaneously, and the problem of high storage capacity in the modified min-max wind power dispatching method is resolved by utilizing the limited min-max wind power dispatching method. The optimal types and capacity of HESS are determined based on multi-objective optimization function with objectives of maximizing the net present value and storage lifetime. Furthermore, in short-term power management control, the wind-HESS performance and delivering the prescheduled and constant power to the network are investigated and HESS charge-discharge cycles are controlled to work in safety range. Finally, the proposed method and short-term power management are evaluated by a wind farm real data, which is scaled down to 3 MW power level for better comparison with other studies.

keywords: *Energy storage optimal sizing, wind-HESS system, multi-objective optimization function, NSGA-II method, short-term power management control*

http://dx.doi.org/10.22109/jemt.2021.261093.1268

NOMENCLATURE

i Index for hourly time interval [1: n]
j Index for ESS type or group [1:2]
N Wind farm lifetime (yr)
T_d Dispatching time interval (hr)
Δt Discrete sample time duration (min)
SoC_{Lj} SoC lower limit of ESS type j
SoC_{Uj} SoC upper limit of ESS type j
η_{cj},η_{dj} Charge/discharge efficiency of energy storage type j
$P_W^i(t)$ Wind power at hour i, minute t (kW)
$P_{W,Lim}^i(t)$ Limited wind power at hour i, minute t (kW)
P_d^i Prescheduled delivered power to the network at hour i (kW)
P_{sj},E_{sj} Nominal power/energy of ESS type j (kW/kWh)
P_{basic}^{Stgj} Storage basic power of ESS type j (kW)
E_{basic}^{Stgj} Storage basic energy of ESS type j (kWh)
E_{opt_1} The first ESS optimal energy (kWh)
$P_{Stgj}^i(t)$ Power value of ESS type j at hour i, minute t (kW)
$E_{Stgj}^i(t)$ energy value of ESS type j at hour i, minute t (kWh)
$P_{Stgj}^{ch,i}(t)$ Charge power of ESS type j at hour i, minute t (kW)
$P_{Stgj}^{dis,i}(t)$ Discharge power of energy storage type j at hour i, minute t (kW)
$SoC_{Stgj}^i(t)$ SoC value of energy storage type j at hour i, minute t
SoC_{0_j} Initial value of SoC of ESS type j
$Profit_{Tot}$ Total profit from wind power sale
c_j total number of charge-discharge cycles of ESS type j in the time period T

1. INTRODUCTION

The penetration of renewable energy sources (RESs) provides numerous benefits in power supply including low pollution, economic advantage, reliability enhancement, power loss reduction. However, the higher levels of RESs penetration due to their intermittent nature may cause negative effects on power stability, system voltage, overall power quality, and power system control [1]. Furthermore, the transmission system operators (TSOs) are faced with serious issues due to increasing loads and the growing use of RESs [2].

In power generation units whose energy sources are intermittent and variable, such as photovoltaic systems and wind farms (WFs), the integration of energy storage systems (ESSs) with them leads to power fluctuations damping [3]. By adding ESSs to non-scheduled units, they may change to dispatchable units. An ESS makes possible the integration of large and variable RESs with other dispatchable generation units and increases the reliability of the network [4]. Furthermore, an ESS absorbs the mismatch between supply and demand powers; especially in micro grids equipped with power electronics converters

In the modern and deregulated electrical power market, all generation units are forced to submit their output power program in the next hours to TSO and to be committed to it [5]. By increasing the penetration percentage of WFs, as a recent solution, utilization of ESSs as energy buffers has been taken into consideration to mitigate power fluctuations of wind farms and manage the wind farms output power in hourly scale [6]. The key factor in the ESS price is energy capacity rating and the ESS sizing is influenced by power management method. Much research has been done based on various optimization methods such as swine influenza model based optimization with quarantine (SIMBO-Q), a new random search method and mixed integer programming (MIP) [7–9] . Reference [10] determines the time constant of a low pass filter and the size of ESS in order to compensate the wind power high frequency fluctuations and maintain the active power fluctuations within an acceptable range, specified by the power network. The bigger time constant provides more power smoothening, while increasing the battery cost.

Reference [11] determines the size of ESS based on prediction of the hourly average wind power generation to minimize deviations from the predicted hourly average wind power that has been announced to TSO as output power in the next hour. Reference [12] proposes a min-max wind power dispatching method based on long-term wind speed data to determine the optimal size of battery which maximizes lifetime to unit cost ratio. In this power management method, delivered power to the network is assigned to the minimum value of producible wind power, when the battery is in charging mode, whereas if the battery experiences discharging mode, the delivered power to the network is set to maximum value of producible wind power. Then, in order to achieve a specified confidence level of delivered wind power, the short-term power management strategy of the WF is extracted by using the wind power short-term prediction. By this scheme, the wind power can be dispatched by the use of a battery, whereas the battery should follow full charge-discharge cycles. Because of larger battery rating and complicated sizing determination program, [13] proposes a modified min-max wind power dispatching method. Also, the optimal battery capacity and delivered power to the network in the next hour are determined based on a new lifetime cost function. This power management algorithm enables the operator to use the battery effectively by maintaining its state of the charge (SoC) in a safety range.

According to [14] the storage device, which is designed by min-max dispatching method [12–15] has the largest capacity in compare to other existing methods. The proposed method in [13] is the same method in [15], however their proposed method decreases the required capacity of ESS in compared to [12], but this capacity is still large and can be further reduced. Reference [16] resolves the problem of large battery capacity in [13] by presenting the limited min-max wind power dispatching method. The achieved net present value (NPV) as objective function of a mixed-integer linear programing (MILP) problem is maximized with smaller ESSs sizes through using hybrid energy storage system (HESS). In addition, the lifetime of ESSs is prolonged by considering their replacement cost. Also, a new clustering technique for input data reduction purpose is used in [16].

In this paper, with respect to benefits of the limited min-max wind power dispatching method [16] compared to other methods, a new sizing process is proposed based on this method, which utilizes an accurate data as input data instead of the reduced data. So that, at first, the basic capacity of ESSs is determined by the introduced power dispatching method in [13] using accurate data of the whole year. Then, by proposing the multi-objective optimization problem and using the limited min-max wind power dispatching method, the optimal energy capacity of main ESS is calculated while the expended lifetime function is minimized and achieved net present value (NPV) is maximized. We consider 13 various types of ESSs and the optimal sizing and technology selection of HESS are performed. This paper contributes to the existing literature as follows:

1) Using accurate data of the whole year, the optimal types and size of HESS are determined by multi-objective optimization problem, which maximizes the NPV and prolongs the ESS lifetime.

2) Short-term power management evaluates the commitment to the announced power to the network through forecasting the wind power at the next hour. The ESS2 compensates forecast error and the SoC of main ESS is maintained in a safety range.

The rest of this paper is organized as follows. Section 2 presents the methodology including the limited min-max power management method, which decreases the size of designed storage devices. The proposed sizing procedures for ESS1 and ESS2 are brought in section 3. In addition, the multi-objective optimization problem and its objective functions for calculating the optimal types and capacity of HESS are described in this section. Section 4 investigates the short-term power management issue and commitment to the problem constraints. Finally, section 5 demonstrates the possibility of implementing the limited min-max power management method and the optimal types and capacity of HESS are determined for a case study with real wind power data. Section 6 concludes this paper.

2. LIMITED MIN-MAX WIND POWER DISPATCHING METHOD

According to the limited min-max wind power dispatching method [16], the prescheduled delivered power to the network at hour i is set to the minimum value of the limited wind power, if ESS1 charges, whereas if this storage is in discharging phase, P_d^i is set to the maximum value of $P_{W,Lim}^i(t)$. Two groups of ESSs implement the proposed power management method as shown in Fig. 1. ESS1 implements the introduced wind power dispatching method in [13] based on the limited wind power and ESS2 compensates the out-of-range wind power. As a result, the size of ESS1 as the main ESS is decreased by neglecting the wind power levels away from its mean value in each time interval that led to larger size of storage designed by the modified min-max dispatching method. Actually, ESS2 limits and compensates the high frequency wind power fluctuations by defined maximum and minimum limits in each time interval. In the following, the

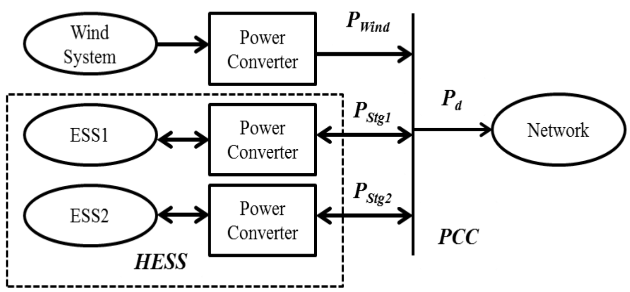

Fig. 1. Configuration of a grid-connected wind system equipped with HESS [16].

calculation process of limited wind power in [16] is reviewed and explained.

A. Upper and Lower Limits Determination of Wind Power

The wind speed varies unstably and is dependent on meteorological conditions. Therefore, the wind power generation is a non-scheduled power. The mean (μ) and standard deviation (σ) of wind power per hour can be calculated using statistical data or forecasted hourly wind power. Thus, the upper and lower limits of wind power at every hour are defined and the limited wind power is calculated as follows:

$$P^i_{W,Lim}(t) = \begin{cases} \mu^i + \sigma^i & \text{if } P^i_W(t) > \mu^i + \sigma^i \\ \mu^i - \sigma^i & \text{if } P^i_W(t) < \mu^i - \sigma^i \\ P^i_W(t) & otherwise \end{cases} \tag{1}$$

It is assumed that , and if T and Td are assumed one hour and one year, respectively. Proportional to wind power fluctuations, these limits are adjusted online to optimize the charging and discharging values of ESS2. By limiting the wind power to the upper and lower limits, the variation of wind power is restricted and $P^i_{W,Lim}(t)$ is calculated as the reference power for limited min-max wind power dispatching method. Then, in an hourly time interval, P^i_d can be determined as follows:

$$P^i_d = \begin{cases} Max\{P^i_{W,Lim}(t)\} = \mu^i + \sigma^i & \text{if } \textit{ESS1 is discharged} \\ Min\{P^i_{W,Lim}(t)\} = \mu^i - \sigma^i & \text{if } \textit{ESS1 is charged} \end{cases} \tag{2}$$

To implement the limited min-max wind power dispatching method, the wind power outside the range of lower and upper limits will be absorbed from or injected into the network by ESS2.

3. DETERMINATION OF CAPACITY AND TYPES OF ENERGY STORAGE SYSTEMS

A. The Required Capacity Definition of Storage Devices

The required capacity of storage in terms of the nominal power and nominal energy can be determined based on the storage power flow. If the power losses can be neglected in the system, the power values of ESS1 and ESS2 at hour i and minute t are defined as follows:

$$P^i_{stg1}(t) = P^i_d - P^i_{W,Lim}(t) \tag{3}$$

$$P^i_{stg2}(t) = \begin{cases} Min\{P^i_{W,Lim}(t)\} - P^i_W(t) & \text{if } P^i_W(t) < Min\{P^i_{W,Lim}(t)\} \\ Max\{P^i_{W,Lim}(t)\} - P^i_W(t) & \text{if } P^i_W(t) > Max\{P^i_{W,Lim}(t)\} \end{cases} \tag{4}$$

Storage power is positive during discharging mode, such as a power source and is negative during charging mode, such as a load. The energy of ESS type j at hour i and minute t considering its charging and discharging efficiencies is determined as (5):

$$E^i_{Stg_j}(t) = \begin{cases} E^{i-1}_{Stg_j}(t-\Delta t) + \eta_{c_j} \times P^{ch,i}_{Stg_j}(t) \times \Delta t \\ \quad +(P^{dis,i}_{Stg_j}(t) \times \Delta t)/\eta_{d_j} \\ \quad \textit{if } t = (i-1)T_d \\ E^{i}_{Stg_j}(t-\Delta t) + \eta_{c_j} \times P^{ch,i}_{Stg_j}(t) \times \Delta t \\ \quad +(P^{dis,i}_{Stg_j}(t) \times \Delta t)/\eta_{d_j} \\ \quad \textit{if } (i-1)T_d < t < iT_d \end{cases} \tag{5}$$

The nominal power and energy of ESS type j are defined as (6) and (7) with respect to the SoC range for $1 \le i \le n, 0 \le t < T$ [17].

$$P_{s_j} = Max\{|P^{ch,i}_{Stg_j}(t)|, P^{dis,i}_{Stg_j}(t)\} \tag{6}$$

$$E_{s_j} = \frac{(Max\{E^i_{Stg_j}(t)\} - Min\{E^i_{Stg_j}(t)\})}{SoC_{U_j} - SoC_{L_j}} \tag{7}$$

B. Basic Capacity of Energy Storage Systems

Prior to determining the optimal capacity of storage system, it is necessary to obtain basic capacity of ESSs by means of long-term wind power data. The basic capacity of both storage systems must be determined based on the limited wind power. Then, the appropriate types of each storage device can be proposed according to the calculated basic capacity. In this paper, the process of basic capacity calculations of ESS in [13] is modified as follow to utilize in accordance with the limited min-max wind power dispatching method.

For determining the basic capacity of ESSs, first, for n wind power data sets with duration of Td, the mean and standard deviation are calculated in each time interval i and wind power is limited to the upper and lower power limits. Thus, $P^i_{W,Lim}(t)$ is considered as reference power in calculations, instead of wind power data. In the proposed process for ESSs sizing, the minimum value of required capacity is defined as a basic capacity and ESS1 will be only in charging or discharging phase in each time interval i. Therefore, the basic power and basic energy of ESS1 should be sufficient so that over-charging or over-discharging does not occur at any time. Duration of time interval i is effective on the amount of ESSs basic capacity and Td is typically determined by TSO in one-hour scale. The determination process of ESSs basic capacity in [13] is modified as follows to be used in the limited min-max wind power dispatching method [16]:

1) First, assume ESS1 is in charging phase at all one-hour intervals during time period T. Thus, the delivered power to TSO is set in the minimum value of the limited wind power and ESS1 must be able to charge with the amount of power difference according to (3).

2) The maximum value of absolute of the calculated power and energy for all one-hour intervals during long-term wind power data will be the basic capacity of storage system in the case of charging during time period T.

3) Similarly, assume that ESS1 is in discharging phase at all

one-hour intervals during time period T. Thus, the delivered power to TSO is set in the maximum value of the limited wind power and storage system must be able to discharge with the amount of power difference according to (3).

4) The maximum value of the calculated power and energy for all one-hour intervals during time period T will be the basic capacity of storage system in the case of discharging during time period T.

5) Finally, the maximum value of obtained basic power and energy in the case of charging and discharging (steps 2 and 4) between all one-hour intervals during time period T will be the basic capacity of ESS1 in charging and discharging modes.

Fig. 2 indicates the flowchart of mentioned steps. According to (4), the task of ESS2 is absorption of power values more than upper limit and injection of power values less than lower limit of $P^i_{W,Lim}(t)$. Thus, according to (6) and (7), the maximum value of absolute of absorbed or injected power and difference between maximum and minimum values of energy at all one hour intervals during time period T divide by the SoC range will be the basic capacity of ESS2 as shown in Fig. 3.

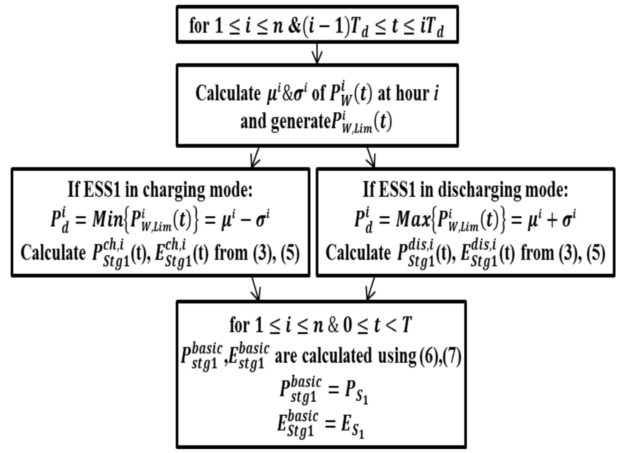

Fig. 2. Flowchart of determination method of ESS1 basic capacity.

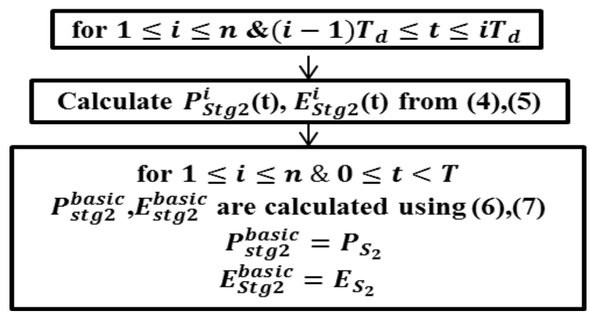

Fig. 3. Flowchart of determination method of ESS2 basic capacity.

C. Optimal Capacity of Main Storage and Optimization Methodology

In this section, the process of optimal sizing and technology selection of HESS is explained. The basic capacity of ESSs only ensures that the wind-HESS system can be integrated into power network in accordance with the limited min-max wind power dispatching method. For a given WF that wind turbines and power electronic converters have already been installed, the operation cost changes based on the cost of storage systems and this cost depends on the initial investment cost and the ESSs lifetime.

When, the storage capacity increases by increasing the factor k, the charging and discharging phases become longer and therefore the ESS lifetime is prolonged, however its cost also increases. Hence, the multi-objective optimization function is looking for the optimal types and capacity of ESSs, which maximize NPV and ESS1 lifetime by examining the storage capacity more than the basic capacity through changing the factor k for ESS1 to find k_{opt} as follows:

$$E_{opt_1} = k_{opt} \times E^{basic}_{Stg_1} \tag{8}$$

The value of factor k is varied as 1<k<6, because for k>6, the main ESS capacity will be greater than the rated generated wind power. Following, the objective functions and the applied multi-objective optimization method will be introduced. The important objective in problem of optimal capacity determination of ESS1 is the system economic evaluation, so that enhancement of the storage lifetime is guaranteed by reducing the number of charge-discharge cycles. As a result, the system cost and the number of main storage charge-discharge cycles are simultaneously minimized to find the optimal size of ESS1 with the highest NPV and lifespan.

C.1. First objective function; net present value

The first objective is maximizing the achieved NPV, which is the difference between the present value of earned profit from selling the generated electricity by WF-HESS system and the present value of costs related to the storage devices. Thus, NPV maximizing is equivalent to maximization of the profit of selling the wind power and minimization of the cost of using the ESSs. In engineering economic science, NPV is one of the standard methods in economic projects assessment. In this method, cash flow of revenues and costs is discounted into present value based on the time value of money. Thus in cash flow, the time of spending money or achieving revenue is also considered. This function is calculated as [18].

$$NPV = Profit_{Tot} - Cost_{Tot} \tag{9}$$

The NPV consists of two terms, which are explained separately as follows:

- Total profit of selling the dispatchable wind power
- Total cost of system equipment

To calculate first term, it is necessary to know that the price of electricity varies in different regions and the governments determine it in some countries. The type of pricing in some cities of China is based on the retail prices, so that in this paper, constant electricity prices are used in pricing of the electricity sold to the network. A day is divided into several time intervals with different energy prices. Electricity price within the period of 9:00–23:00 is assumed 0.8 RMB/kWh, and the price of the rest period is 0.4 RMB/kWh [19]. The earned profit from selling electricity to the network is calculated for year one of the studied system. Thus, the total profit from selling electricity over the WF lifetime (N) with respect to definition of present value function (PVF) can be expressed as follows

$$Profit_{Tot} = (\sum_{i=1}^{n} P_d^i \times \lambda_C^i) \times PVF(Intr, Infr, N) \quad \textbf{(10)}$$

Where, λ_C^i is the selling price of electricity at hour i and Intr and Infr represent interest and inflation rates, respectively. Then, to calculate the second term, it is worth to mention the main cost of the studied wind-HESS is the price of wind turbines and ESSs. In a WF where wind generation units have already been installed and the goal is to determine the optimal types and capacity of storage systems, minimizing the cost of installation of installed equipment cannot be considered in the cost function. Thus, the total cost function is defined as follows:

$$Cost_{Tot} = \sum_{j=1}^{2} IC_{Stg_j} + \sum_{j=1}^{2} OM_{Stg_j} + \sum_{j=1}^{2} RC_{Stg_j} \quad \textbf{(11)}$$

Where,IC_{Stg_j} is related to storage system cost and cost of power electronic converter, which is connected to it and OM_{Stg_j} is the total operation and maintenance cost of storage type j during the WF lifetime. Different types of ESSs can be charged and discharged in a certain number of cycles during their lifetime. If the lifespan of storage systems is less than the lifespan of wind turbines, it is necessary that these systems be replaced several times during the wind systems lifetime. The replacement time of any storage system type j (T_{R_j}) and number of replacement (N_{R_j}) during lifetime of WF can be calculated by counting charge-discharge cycles of storage device. RC_{Stg_j} is cost of replacement. Refer to [16] for more explanations about calculating the Total Cost's terms.

C.2. Second objective function; expended lifetime function

Based on the proposed power management method in [16], ESS1 is only charged or discharged at every hour and the total number of charge-discharge cycles of ESS1 is countable. A reduction in number of charge-discharge cycles provides better health state of battery energy storage and prolongs its lifetime. Thus the second objective is reducing the number of charge-discharge cycles of main ESS during the operation period to increase its lifetime. The one-year expended lifetime function (LT %) is used as percentage of the used lifetime of ESS in one year, so that the optimal storage capacity will be determined for implementing the limited min-max wind power dispatching method by minimizing the amount of this function as follows:

$$LT_{1yr_j} = \frac{c_1}{C_{l_1}} \times 100 \quad \textbf{(12)}$$

Where, C_{l_1} is the storage life cycle or total number of full charge-discharge cycles of ESS1 during its lifetime respect to the defined DoD. Also N_{R_j} and T_{R_j} for ESS type j are determined as:

$$N_{R_j} = N \times LT_{1yr_j} \quad \textbf{(13)}$$

$$T_{R_j} = \frac{1}{LT_{1yr_j}} \quad \textbf{(14)}$$

C.3. Multi-objective optimization method

The most important difference between single-objective and multi-objective optimization is the possibility of existing multiple practical answers, which satisfy the optimization indices. Besides, it may be possible that a set of equally good solutions exist in multi-objective optimization problems which do not have any superiority over each other, whereas only one answer is expected in a single-objective optimization problems. Multi-objective optimization results can be considered as a set of non-dominated solutions called Pareto front. The obtained Pareto front from solving the optimization problem is actually a trade-off between NPV and storage lifetime.

Multi-objective genetic algorithm (MOGA) as optimization algorithm or searching method is used to find a set of equally good solutions or Pareto front to achieve the intended objectives. Although other optimization methods can also be used, this method is one of the most popular heuristic search techniques in multi-objective optimization problems. The genetic algorithm (GA) is the core of MOGA optimization and uses two crossover and mutation operators to find the next children population. The non-dominated sorting and crowding distance are utilized as two new and important concepts in order to calculate the member ranking. By considering the particular method in sorting, this algorithm has conditions superior to the first version MOGA. Because of using GA and two new concepts mentioned above, MOGA is also called non-dominated sorting genetic algorithm-II (NSGA-II) [20].

D. Optimal Types of Energy Storage Systems

According to the calculated basic capacity and the desired tasks for each storage device, the suitable type for the main storage, which should have high energy capacity, includes all types of batteries, compressed air storage system (CAES) and pumped hydroelectric storage (PHES). Whereas, the appropriate type for ESS2 should have high ramp power rate and be able to charge and discharge frequently to compensate power fluctuations quickly. As a result, conventional batteries except lead-acid, current batteries and special storage systems with short time scale such as super capacitor (SC), flywheel, and super magnetic energy storage (SMES) are appropriate types [21]. Average value of costs and structural characteristics of mentioned appropriate types for HESS can be found in [16], [22–24]. The multi-objective problem is solved for each of appropriate types of ESS1 and ESS2 and the optimal types of HESS are determined based on maximum achieved NPV while the expended lifetime function is minimized, simultaneously.

4. SHORT-TERM POWER MANAGEMENT CONTROL

The most important issue in wind-HESS system is the short-term power management control. According to the described process, the optimal types and capacity of HESS are determined based on the available long-term wind power data. In addition, based on the minimum and maximum levels of limited wind power, the power management method is implemented in each dispatching time interval. It is necessary to forecast wind power data in the short-term power management and during scheduling time of delivered power in each hourly time interval.

Thus, this forecasted data is not exactly known in contrast to long-term data and in this case, ESS2 can compensate the forecast error in predetermined delivered power beside its main task. If the main storage is full charged or discharged due to the forecast errors, ESS2 absorbs from WF or injects into network the wind power surplus or shortage compared to P_d^i, for commitment to the prescheduled delivered power. Furthermore, in the short-term management, an on-line SoC control is employed to manage charge-discharge period of storage system.

A. Online Control of State of Charge

The delivered power to the network at hour i will be equal to the minimum or maximum of the limited forecasted wind power, if ESS1 has been in charge or discharge phase in the previous time interval, respectively. The limitation of charging and discharging states of storage is an important and considerable issue in controlling the SoC of storage type j to maintain in a safe range as follows:

$$SoC_{L_j} \leq SoC^i_{Stg_j}(t) \leq SoC_{U_j} \quad \textbf{(15)}$$

In the batteries, the SoC range for optimum performance usually is defined between 0.2-0.8, nevertheless using the range of 0.1-0.9 dose not damage battery lifetime seriously [25]. If the initial SoC is known, $SoC^i_{Stg_j}(t)$ is determined through (16) whether storage is charged or discharged.

$$SoC^i_{Stg_j}(t) = SoC_{0_j} - E^i_{Stg_j}(t)/E_{S_j} \quad \textbf{(16)}$$

The online control algorithm of SoC calculates the SoC value based on predetermined delivered power in the next time interval and makes decision about storage charge or discharge phase according to (15). If SoC limitation is not provided, charge or discharge phase of ESS1 will be different in time interval i from the previous time interval. Thus, the storage charge level is controlled in a manner that satisfies the power management objectives. The proposed power management method is applied at the start of each new time interval and the ESS continues its work in charging or discharging phase with respect to charge or discharge mode of the previous power management interval.

5. CASE STUDY AND ANALYSIS

In this section, the described procedures of sizing and technology selection of HESS and limited min-max wind power dispatching method are implemented on a case study to evaluate their performances in a WF equipped with HESS. A real wind power profile of a 245 MW wind farm in the year 2015 has been downloaded from [26] and has been scaled down to 3 MW power level with one minute sample time (i.e., T=1 year and Δ t=1 minute). Deep discharging and over charging can damage and shorten the ESS lifetime. Thus, in order to prolong the storage lifetime, the SoC range of ESS1 (in the case of batteries) is kept between 0.2 and 0.9 and the DoD of storage and the SoC range are 80% and 0.7, respectively

Also, the SoC range of the ESS2 is set between 0.05 and 0.95. The SoC_0 values of ESS1 and ESS2 are equal to 0.57 and 0.5, respectively. Td is considered one hour as dictated by TSO and the interest rate and inflation rate are assumed 10% and 7% [22]. A simulation program for HESS sizing and selection procedures is implemented using MATLAB 2014 software.

A. Calculation of Basic Capacity of Energy Storage Systems

Initially, the hourly mean and standard deviation of wind power profile are calculated for the one-year data of the studied WF. Then, the limited wind power profile is generated by limiting the wind power generation to the upper and lower limits. The ESS1 compensates the limited wind power compared to the announced power that must be delivered to the network and the basic capacity of ESS1 is determined according to the mentioned steps in section 3.2.

To explain these steps more clearly, for example, a wind power profile is considered in the last 12 hours of one day. According to Fig. 4a, if ESS1 discharges at every hour, the delivered power to the network is equal to the maximum value of limited wind power at every hour. Fig. 4b and Fig. 4c indicate ESS1 power and energy in discharging phase, respectively. The maximum values of power and energy occur in fifth dispatch interval and ESS1 basic power and energy in discharging phase are equal to 562.8 kW and 446.2kWh, respectively.

During the charging phase of ESS1, the delivered power to the network is set to the minimum value of limited wind power at every hour as Fig. 5a-Fig. 5c depict power and energy of ESS1 in charging phase, respectively. The maximum value of absolute of power and energy occur in fifth dispatch interval and the basic power and energy of ESS1 in charging phase are defined 562.8 kW and 344.4 kWh, respectively.

By implementing the limited min-max wind power dispatching method for the studied wind power data in a 12-hour period, the basic power and energy of ESS1 is equal to the bigger value of them in two charge and discharge phases and calculated 562.8 kW and 446.2 kWh. ESS2 absorbs power values more than upper limit of limited wind power and injects power values less than the lower limit of limited wind power. Fig. 6 illustrates the power and energy diagram of ESS2 and according to the given explanations, its basic power and energy for the studied time interval are 263.06 kW and 75.8 kWh, respectively. If the explained process is applied to one-year wind power profile of the case study, the values of basic capacity for HESS are equal to:
$P^{basic}_{Stg1} = 563kW, E^{basic}_{Stg1} = 446kWh, P^{basic}_{Stg2} = 420kW, E^{basic}_{Stg2} = 205kWh$

B. Calculation of Basic Capacity of Energy Storage Systems

After calculating the basic power and energy for HESS, by using one-year data of wind power generation, the optimal capacity of ESS1 and optimal HESS types are determined. Initially, it is necessary to solve the multi-objective optimization problem with objectives including maximizing the NPV and storage lifetime by increasing the factor k from 1 to 6 in (8) for ESS1 to find k_{opt} which satisfies the objective functions.

For this purpose, we use NSGA-II method in MATLAB environment with 50 initial members. To find the next children population, the probabilities of crossover and mutation operators are considered 0.8 and 0.2, respectively. Also, the mutation rate and mutation step size are defined 0.02 and 0.1, respectively. With constraints 1<k<6 and (15), the multi-objective optimization problem is solved and among the obtained Pareto front, the maximum value of NPV for the proposed various types of ESSs (as section 3.3) is calculated considering their lifetime and replacement time.

At the next step, a search for the optimal technology selection for HESS is done and these results are compared together. Table 1 indicates the optimization results for choosing different types of HESS among any of the possible options. Each technology for ESS1 and ESS2 that brings maximum NPV while the one-year expended lifetime function (LT%) is minimized at the same time, will be selected as optimal HESS and in this case, the used factor k will be k_{opt}. The top three most profitable selections are related to use of the following storage systems as the ESS1 and ESS2, respectively

- PHES and SC
- ZnBr battery and SC
- CAES (underground) and SC

A PHES needs the specific area and special location for higher and lower reservoirs. Its weaknesses are the geographical constraints and high initial cost while the repair cost is very low. Therefore, by considering environmental constraints and cost reduction of batteries [27], the optimal selection for ESS1 and ESS2 is the combination of ZnBr battery and SC, respectively.

In this case, the optimal capacity of ESS1 for k_{opt}=1.447 is 645.7 kWh. Meanwhile, flywheel is the next rank for optimal selection of ESS2. Fig. 7 indicates a sample of obtained Pareto front for ZnBr battery and SC as ESS1 and ESS2. Point A indicates the maximum value of obtained NPV. In the batteries, if depth of discharge (DoD) becomes deeper, the storage life cycle (Cl) will be shorter and significantly influences the battery lifetime. The rated DoD of 80% is assumed for determining the storage section cost ($/kWh) for all batteries whereas ZnBr has a 100% DoD capability on a daily basis and is not damaged, but improves [28].

C. Validation of the Required Capacity of Storage Devices

To validate the achieved results, using the studied wind power generation and ZnBr battery data, the basic power and energy values of ESS are computed based on the modified min-max method in [13]. For SoC range equal to 0.7, the basic power and energy are obtained 1001.6 kW and 945.1 kWh, respectively. Also, according to [13], the optimal battery capacity is defined kopt times of the basic energy (i.e., $4 \times 945.1 = 3780.4$ kWh), while the calculated overall power and overall optimal energy for two ESSs based on the limited min-max wind power dispatching method are equal to 983 kW and 850.7 kWh, respectively. Actually, the use of ESS2 reduces the power rating and energy capacity of ESS1 and as a result, the overall cost is decreased. Table 2 shows these results.

According to Table 2, using the limited min-max power management method and HESS, lower power and energy capacity as well as lower cost will be required to control WFs output power while the advantages of HESS are achieved at the same time. As a result, the problem of high capacity of ESS in the modified min-max wind power dispatching method will be resolved similar to [16] using the proposed optimal sizing process.

D. Short-Term Power Management Control

In this section, short-term power management and performance of wind-HESS system are discussed to ensure the proper system operation in implementing the limited min-max wind power management method with optimal HESS designed. The hourly scheduled power should be delivered to TSO while the SoC constraint in (15) is satisfied, as well. It is necessary to forecast the wind power at the next hour using an appropriate prediction method to calculate the hourly mean and standard deviation of wind power and determine the limited wind power and the next hour delivered power to TSO. For this purpose, the real wind power data in one day ($31_{th} Jan.$2018) is utilized and is forecasted in hourly scale. This day is intentionally selected to indicate the task of ESS2 in compensating the wind power forecast error. Fig. 8a indicates the limited forecasted wind power, upper and lower limits of forecasted wind power and limited real wind power.

Thus, the short-term power management control is evaluated by forecasting the wind power at the next hour. For this purpose, a radial basis functions (RBF) neural network with 50 neurons is employed [29]. 70% data is used for training and other data is considered as the test data. The prescheduled and delivered power to the network and SoC variations are shown in Fig. 8b. According to (15), the SoC range of the ESS1 and ESS2 at any hourly interval must be maintained within a certain range (i.e., 0.2-0.9 and 0.05-0.95) and P_d^i must be delivered at any hour as announced schedule.

It is assumed that at 00:00AM and at the beginning of an hourly scheduled interval, the phase of main ESS changes from discharging to charging. According to Fig. 8b, the SoC variations of HESS are maintained in a safe range, whereas the hourly scheduled power that has been determined based on the forecasted wind power is delivered to TSO at any hour without any error. Thus, the limited min-max wind power dispatching method is successfully implemented at all hours.

In Fig. 8b, according forecasted wind power, the main ESS must be charged at hour 14:00 and $P_d^i(t)$ has been set to minimum value of $P_{W,Lim}^i$. Nevertheless, in 14:18', the main ESS charging is stopped to maintain the SoC in a safe range and ESS2 is charged to SoC value of 0.94. Thus, ESS2 compensates the forecast error as well as absorbs or injects the outside wind power of the range of limited wind power. Fig. 8c and Fig. 8d indicate power and energy of ESS2 such that none of them exceed of nominal values.

Table 1. Simulation results for different types of ESSs.

Type of ESS1 / Type of ESS2	Parameters	SC	Flywheel	SMES
PHES	NPV(M$)	9.072	8.807	7.672
	LT(%)	3.032	3.268	2.936
	k_{opt}	1.09	1.018	1.121
ZnBr battery	NPV(M$)	8.854	8.608	7.476
	LT(%)	9.553	9.881	9.991
	k_{opt}	1.447	1.427	1.41
CAES (underground)	NPV(M$)	8.814	8.546	7.411
	LT(%)	2.676	2.396	2.396
	k_{opt}	1.207	1.321	1.321
CAES (aboveground)	NPV(M$)	8.805	8.541	7.405
	LT(%)	3.288	3.328	3.296
	k_{opt}	1.007	1.004	1.013
NaS battery	NPV(M$)	8.772	8.507	7.367
	LT(%)	19.97	19.97	19.93
	k_{opt}	1.35	1.35	1.355
VRB battery	NPV(M$)	8.606	8.356	7.217
	LT(%)	24.01	25	24.69
	k_{opt}	1.157	1.112	1.131
Lead-Acid battery	NPV(M$)	8.552	8.345	7.161
	LT(%)	24.9	24.97	24.86
	k_{opt}	1.127	1.12	1.115
NiCd battery	NPV(M$)	8.135	7.875	6.739
	LT(%)	19.89	19.95	19.92
	k_{opt}	1.117	1.11	1.111
Li-Ion battery	NPV(M$)	7.853	7.584	6.454
	LT(%)	24.98	24.93	24.98
	k_{opt}	1.442	1.443	1.442
H2	NPV(M$)	7.594	7.333	6.195
	LT(%)	4	4.095	4.03
	k_{opt}	1.018	1.002	1.008

6. CONCLUSION

In this paper, a new sizing process based on the limited min-max wind power management method was proposed to dispatch

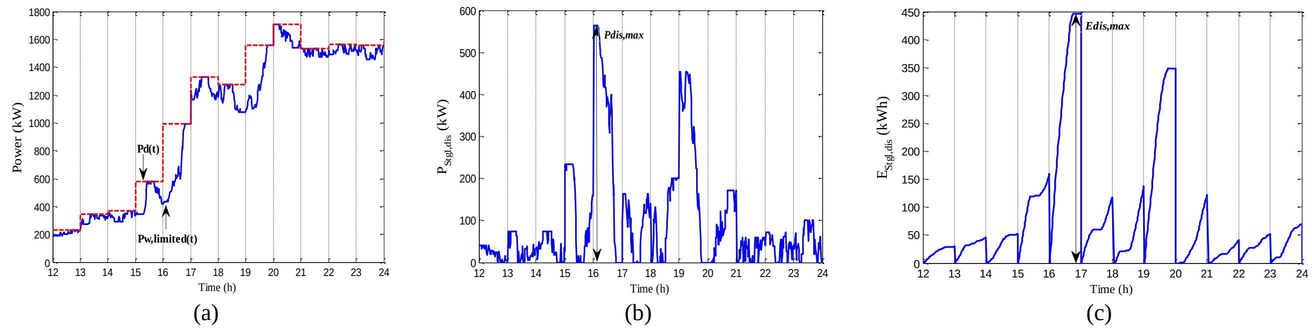

Fig. 4. Determination of basic capacity in discharging phase. (a) Limited wind power and scheduled delivery power, (b) Discharge power of main ESS, (c) Discharge energy of main ESS.

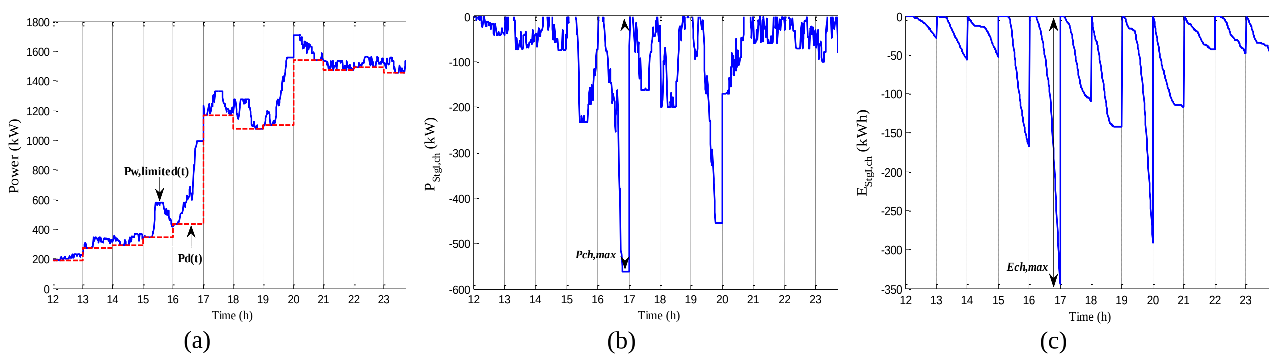

Fig. 5. Determination of basic capacity in charging phase. (a) Limited wind power and scheduled delivery power, (b) Charge power of main ESS, (c) Charge energy of main ESS.

Table 2. Required ESSs power and optimal energy

Wind power dispatching methods	NPV(M$)	ESSs Power #1 (kW)	ESSs Power #2 (kW)	Total	ESSs Energy #1 (kWh)	ESSs Energy #2 (kWh)	Total
Limited min-max(Multi-obj.)	8.854	563	420	**983**	645.7	205	**850.7**
Modified min-max [13]	8.539	1001	-	**1001**	3780	-	**3780**
Limited min- max(MILP) [16]	8.630	502	404	**906**	734	205	**939**

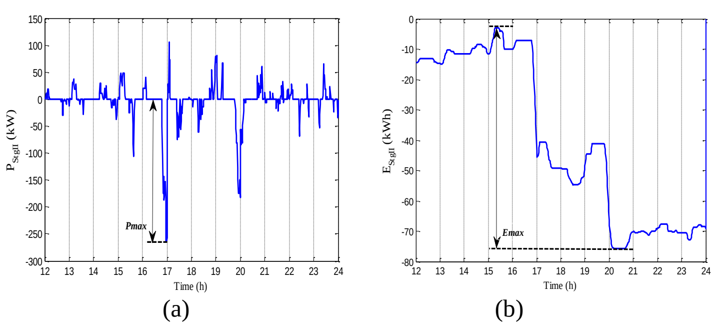

Fig. 6. Determination of basic capacity in charging and discharging phase. (a) Power of ESS2, (b) Energy of ESS2.

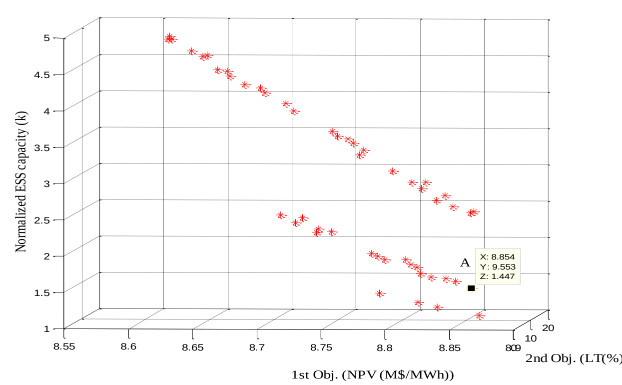

Fig. 7. Obtained Pareto front for ZnBr battery and SC.

the wind power and resolve the problem of high capacity of designed ESS in the modified min-max wind power dispatching method. The hourly power was announced to TSO and was delivered by utilizing HESS with appropriate features. The objectives of maximizing the NPV derived from selling the wind power and the main ESS lifetime were achieved by optimizing

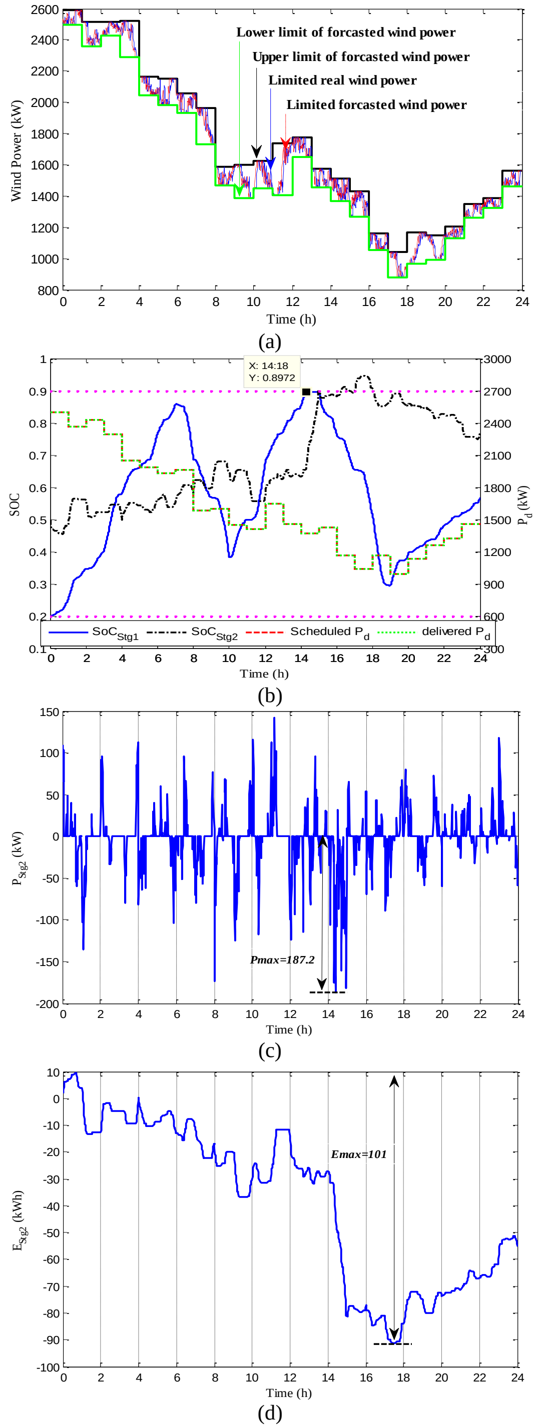

Fig. 8. Short-term power management. (a) Upper and lower limits of forecasted wind power, limited forecasted wind power and limited real wind power, (b) SoC of HESS, scheduled and delivered power, (c) Power of ESS2, (d) Energy of ESS2.

the multi-objective function and determining the HESS optimal types and size. Thus, by using HESS, the advantages of two types of ESSs are achieved including high power and energy capacity, high life-cycle and fast response in the same time.

In addition, by implementing short-term power management based on the forecasted wind power, the possibility of implementing the wind power dispatching method using the designed HESS was demonstrated, whereas the constraints including the commitment to provide the announced power to TSO and maintaining the SoC value of main ESS within the safe range were met by using ESS2. The use of ESS2 led to compensation of uncertainties in hourly forecasted wind power and ensured provision of the scheduled power to TSO. Finally, the ability of the proposed method in dispatching the real wind farm was examined by simulation program using a large number of actual wind power data as input data.

REFERENCES

1. C.A. Sepulveda Rangel, L. Canha, M. Sperandio, R. Severiano, "Methodology for ESS-type selection and optimal energy management in distribution system with DG considering reverse flow limitations and cost penalties," IET Generation, Transmission and Distribution, vol. 12, no. 5, pp. 1164-1170, 2018.
2. F. Islam, A. Al-Durra, S. M. Muyeen, "Smoothing of wind farm output by prediction and supervisory-control-unit-based FESS," IEEE Trans. Sustainable Energy, vol. 4, no. 4, pp. 925-933, 2013.
3. M.R. Jannesar, A. Sedighi, M. Savaghebi, A. Anvari-Moghadam, J. M. Guerrero, "Optimal multi-objective integration of photovoltaic, wind turbine, and battery energy storage in distribution networks," Journal of Energy Management and Technology, vol. 4, no. 4, pp. 76-83, 2020.
4. M. McPherson, S. Tahseen, "Deploying storage assets to facilitate variable renewable energy integration: The impacts of grid flexibility, renewable penetration, and market structure," Energy, vol. 145, pp. 856-870, 2018.
5. D.L. Yao, S.S. Choi, K.J. Tseng, T.T. Lie, "A statistical approach to the design of a dispatchable wind power-battery ESS," IEEE Trans. Energy Conversation, vol. 24, no. 4, pp. 916–925, 2009.
6. A. Kargarian, G. Hug, "Optimal sizing of energy storage systems: a combination of hourly and intra-hour time perspectives," IET Generation, Transmission and Distribution, vol. 10, no. 3, pp. 594-600, 2016.
7. Sh. Sharma, S. Bhattacharjee, A. Bhattacharya, "Swine Influenza model based optimization for operation management of micro-grid," In EESCO, Jan. 2015, Visakhapatnam, India , pp. 1-6.
8. X. Zhang, S. Ch. Tan, G. Li, J. Li, Zh. Feng, "Components sizing of hybrid energy systems via the optimization of power dispatch simulations," Energy, vol. 52, pp. 165-172, Apr. 2013.
9. M. Gitizadeh, H. Fakharzadegan, "Battery capacity determination with respect to optimized energy dispatch schedule in grid-connected photovoltaic (PV) systems," Energy, vol. 65, pp. 665-674, 2014.
10. L. Liang, L. Jianlin, H. Dong, "An optimal energy storage capacity calculation method for 100 MW wind farm," In POWERCON, Oct. 2010, Hangzhou, China, pp. 1-4.
11. S. Teleke, M. Baran, S. Bhattacharya, A.Q. Huang, "Optimal control of battery energy storage for wind farm dispatching," IEEE Trans. Energy Conversation, vol. 25, no. 3, pp. 787–794, 2010.
12. Q. Li, S.S. Choi, Y. Yuan, D.L. Yao, "On the determination of battery energy storage capacity and short-term power dispatch of a wind farm," IEEE Trans. Sustainable Energy, vol. 2, no. 2, pp. 148–158, 2011.
13. C.L. Nguyen, H.H. Lee, T.W. Chun, "Cost optimized battery capacity and short term power dispatch control for wind farm," IEEE Trans. Industry Applications, vol. 51, no. 1, pp. 595-606, 2015.
14. C.L. Nguyen, H.H. Lee, "A comparative analysis among power dispatching control strategies for hybrid wind and energy storage system," In 20th International Conference on Electrical Engineering, Jun. 2014, Jeju, Korea, pp. 489-494.
15. C.L. Nguyen, T.W. Chun, H.H. Lee, "Determination of the optimal battery capacity based on a life time cost function in wind farm," IEEE Energy Conversion Congress and Exposition, pp. 51–58, 2013.
16. M. Khosravi, S. Afsharnia, Sh. Farhangi, "Optimal sizing and technology selection of hybrid energy storage system with novel dispatching power for wind power integration," International Journal of Electrical Power and Energy Systems, vol. 127, May 2021, 106660.

17. X.Y. Wang, D.V. Mahinda, S.S. Choi, "Determination of battery storage capacity in energy buffer for wind farm," IEEE Trans. Energy Conversation, vol. 23, no. 3, pp. 868–878, 2008.
18. A. Berrada, Kh. Loudiyi, I. Zorkani, "Profitability, risk, and financial modeling of energy storage in residential and large scale applications," Energy, vol. 119, pp. 94-109, 2017.
19. H. Ding, Z. Hu, Y. Song, "rolling optimization of wind farm and ESS in electricity markets," IEEE Trans. Power Systems, vol. 30, no. 5, pp. 2676–2684, 2015.
20. B. Zhao, X. Zhang, J. Chen, C. Wang, "Operation optimization of standalone microgrids considering lifetime characteristics of BESS," IEEE Trans. Sustainable Energy, vol. 4, no. 4, pp. 934-943, 2013.
21. M. Moradzadeh, J.V. de Vyver, L. Vandevelde, "Optimal energy storage sizing based on wind curtailment reduction," In ICRERA, Oct. 2014, Milwakuee, USA, pp. 331-335.
22. M. Daghi, M. Sedghi, A. Ahmadian, M. Aliakbar-Golkar, "Factor analysis based optimal storage planning in active distribution network considering different battery technologies," Applied Energy, vol. 183, pp. 456–469, 2016.
23. D.O. Akinyele, R.K. Rayudu, "Review of energy storage technologies for sustainable power networks," Sustainable Energy Technology Assess., vol. 8, pp. 74–91, 2014.
24. B. Zakeri, S. Syri, "Electrical energy storage systems: A comparative life cycle cost analysis," Renewable Sustainable Energy Review, vol. 42, pp. 569–596, 2015.
25. M. Jannati, S.H. Hosseinian, B. Vahidi, G.J. Li, "ADALINE (ADAptive Linear Neuron)-based coordinated control for wind power fluctuation smoothing with reduced BESS (Battery Energy Storage System) capacity," Energy, vol. 101, pp. 1-8, 2016.
26. Wind power Data [Online]. Available: https://www.ceps.cz/en/all-data-GenerationRES.
27. Z. Wang, A. Negash, D.S. Kirschen, "Optimal scheduling of energy storage under forecast uncertainties," IET Generation, Transmission and Distribution, vol. 11, no. 17, pp. 4220-4226, 2017.
28. P.C. Butler, Ph. A. Eidler, P.G. Grimes, S.E. Klassen, R.C. Miles, "Zinc/Bromine batteries," Sandia National Laboratories (SNL), California, 2000 [Online]: www.sandia.gov/ess/publications/SAND2000-0893.pdf.
29. M. Dadkhaha, M.J. Rezaee, A.Z. Chavoshi, "Short-term power output forecasting of hourly operation in power plant based on climate factors and effects of wind direction and wind speed," Energy, vol. 148, pp. 775-788, 2018.
30. F. Dıaz-Gonzalez, F.D. Bianchi, A. Sumper, O.G. Bellmunt, "Control of a flywheel energy storage system for power smoothing in wind power plants," IEEE Trans. Energy Conversation, vol. 29, no. 1, pp. 204-214, 2014.