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Optimal sizing of energy storage system for power grid planning with intermittent wind generations

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***Abstract*—**For power grids with high penetration of intermittent renewable generations, energy storage system (ESS) is a key enabling device for the grid to accommodate the uncertainties of renewables. However, the installation of ESS at a suboptimum size not only increases the one-off installation cost, but also leads to higher long-term operation and maintenance costs. With the concern of capital costs outweighing ESS operating profits, this paper established a stochastic model to determine the optimal size of ESS for the planning of power grids with intermittent wind generations. In the model, the uncertain wind generations were first derived from long-term historical data as 24 hourly-based probabilistic distributions, and then a stochastic model with consideration of the generation fuel expected costs plus the ESS amortized daily capital costs was formed. Compared with the day-by-day time-series deterministic approach, the proposed probabilistic model is general and flexible for long-term power system planning with uncertain wind generations. A hybrid solution approach consisting of the point estimated method and the parallel branch and bound (BB) algorithm was then designed to effectively solve this model. In the case study, the cost-benefits were thoroughly investigated using two modified test systems with 10-unit and 26-unit including four typical ESSs with various key parameters. Simulation results confirmed that the proposed model and solution approach are effective to determine the optimal ESS size in power grids with intermittent wind generations.

***Key Words*—** Sizing of energy storage system; Intermittent wind generation; Unit commitment; Point estimated method; Parallel branch and bound algorithm

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1. INTRODUCTION

Energy conservation is always a popular and timeless issue in power industries, and various energy saving techniques with peak-load shifting capability [1-3] have attracted wide range of interests. With the premise of instantaneously balancing power generations and consumptions, energy storage system (ESS) is often operated to store surplus energy in off-peak hours and release it during energy-deficiency hours such that temporal arbitrages can be obtained via economical scheduling of stored energy.

While extensive researches have been conducted on ESS, they are mainly focused on the following two aspects [4]: 1) the optimal operation of ESS, and 2) the size determination of ESS.

For ESS optimal operation, ESS is usually coupled with conventional generators and renewables to pursuit the maximum benefits for frequency regulation [5-7], oscillation damping control [8,9], voltage control support [10,11], etc. In addition, there are large amount of literatures focusing on conducting effective generation scheduling by using ESS [12-14]. For example, the energy shifting strategy was adopted in [15,16] to effectively dispatch an integrated thermal photovoltaic battery generation system for short-term economic resources allocation. An ancillary service model was proposed in [17] to enable electric vehicle aggregators to provide power utility with load regulation and spinning reserves via V2G such that the maximization of aggregator’s profit is inline with enhanced system flexibility. In [18], a demand response scheme with hybrid electric vehicles was designed for peak load shaving, and the game theory was adopted to solve the Nash equilibrium point to minimize customers’ charging cost. In [19], a security constrained unit commitment (UC) model was presented to arrange the energy and ancillary services of compressed air energy storages with given capacity ratings. Complementary to optimal operating ESS with these deterministic solutions in [15-19], the two-stage stochastic programming model was also developed [20-23] for ESS operation. In [21,22], the joint operation of a hydro pumped-storage and a wind farm was compared with their separated operations in a day-ahead uncertain market. The results indicated that the integrated operation could earn more profits than their separated operations, while the impacts of the pumped-storage size on power market profits were discussed without including any storage capital cost. In [23], a bi-level robust scheduling model was researched for virtual power plant (VPP) considering the wind power uncertainty, price-based and incentive-based demand response, and the results illustrated the model was effective to overcome the influence of uncertainty on VPP operations. In [24], a stochastic approach was presented to determine the optimal energy and reserve bids of a storage unit in a day-ahead and hour-ahead market with random wind generations. The approach deemed the storage unit owned by an independent investor instead of a Generation Company (Genco), and the target was to maximize the independent investor's expected profit for two different biding strategies. While the cost of ESS capacity was roughly discussed in terms of energy biding from independent investors' aspect, the complete cost related to ESS sizing (in terms of both power and capacity) has not been fully considered in its objective.

With concerns on ESS high capital costs outweighing its profits, the determination of ESS size has become an important issue for its practical utilization. In [25], a deterministic approach was proposed to analyze the economic benefit of an ESS during its entire life cycle, and a tabu-search evolutionary algorithm was used to find the appropriate ESS size for a thermal power system. In [26], a Distributed Energy Resources Customer Adoption Model was introduced to determine the optimal size and operating schedules of thermal energy storages, results indicated that thermal energy storages with proper size can be effective to reduce annual electricity costs and peak electricity consumptions. In [27], the price-maker and price-taker approaches were proposed to figure out the optimal planning and management of distributed energy resources with consideration of its participation in the electricity market and its impact on the market price, and the results suggested that the aggregation of distributed energy resources can be very profitable for both aggregators and prosumers. In [28], the feed-forward neural network was used to forecast the solar radiation, then a conventional UC problem was solved to optimize the ESS deployments in micro grids for both grid-connected and islanded operation modes. For micro-grid in [29], a UC formulation including multiple PEM-Fuel Cell power plants was presented to determine the optimum size of typical energy storages with practical constraints satisfied over one day with 15-minute time step. In [30], a mixed integer linear programming model was developed to optimize the area of roof mounted photovoltaic thermal collectors and thermal energy storage volume, and then the model was decomposed into two sub-modules and solved iteratively to minimize the overall energy system cost. [31] adopted the particle swarm optimization (PSO) based frequency control method to evaluate an optimum size of ESS to prevent the micro-grid from instability and system collapse. In [32], a MILP model integrating the daily energy plan with the generation expansion plan was introduced to determine the optimal capacity additions, electricity market clearing prices and daily operational schedules for the Greek power system. In particular, for power grid planning with wind generations and ESS, [33] established a three-stage approach to fix ESS sizing and siting to alleviate transmission network congestions. In the first two stages, the conventional security constrained UC was solved day-by-day for three years based on deterministic hourly wind generation predictions. The optimal size of storage unit was then derived from the average of the daily power and capacity ratings over three years. Since a large series of day-by-day optimizations spanning over many years was conducted to determine the ESS optimal size, this approach would be cumbersome for long-term power system planning with many years' wind generation data.

Because of the inherent stochastic characteristics of wind power, the uncertainties of wind generations should be take into account for determining ESS size in power systems planning problem, and a stochastic model needs to be researched correspondingly [25]. For this purpose, a stochastic cost-benefit model capable of effectively optimizing ESS size coupled with uncertain wind generations is proposed in this paper. Specifically, the probabilistic distribution curves of wind generations are first produced by fitting its historical data over multiple years, then a UC-based stochastic planning model is proposed. In the model, ESS is assumed to be owned by a Genco with objective to minimize Genco's generation fuel costs expectation plus ESS amortized daily capital cost. The proposed stochastic model is then transformed into a deterministic UC problem using Point Estimated (PE) method, and solved by a parallel Branch and Bound (BB) algorithm. The main contributions of the paper are as follows:

1) The probabilistic distributions of hourly wind generations are easily derived from multiple years of wind generation data and readily extended for long-term stochastic power system planning. Compared with the three-stage planning for ESS in [33] based on the day-by-day deterministic optimization over multiple years, in this paper the probabilistic distributions of hourly wind generations are firstly derived from historical data to enable a stochastic cost-benefit model to be proposed to directly optimize ESS size for power system planning.
2) The proposed stochastic cost-benefit model, simultaneously considering the generation fuel cost expectation plus the amortized daily capital cost, is general and flexible for power system planning coupled with intermittent wind generations of various probabilistic characteristics.
3) A parallel Branch and Bound algorithm with Point Estimated strategy incorporated is designed to efficiently solve the proposed model.
4) The effectiveness of the proposed stochastic model and solution approach to determine ESS optimal sizing for power systems with uncertain renewables is demonstrated by two case studies, and the impacts of ESS key parameters on power system cost-benefits are also comprehensively investigated.

The rest of this paper is organized as follows: Section 2 first derives the probabilistic distributions of hourly wind generations from historical data, and then presents the stochastic model to optimize ESS size. Section 3 introduces the PE method to convert the stochastic problem into a set of deterministic UC solved by a parallel BB algorithm. Two modified multiple-unit systems with intermittent wind generations are tested for four typical ESSs, and the impacts of ESS parameters on system cost-benefits are investigated in Section 4. Finally, conclusions and remarks are drawn in Section 5.

2. Problem Formulation

This section proposes the UC-based stochastic cost-benefit model to determine the ESS optimal size for power system planning in presence of uncertain wind generations. Distinguished from the rolling approach with day-by-day deterministic optimizations over multiple years [33], in this paper the stochastic features of wind generations was first extracted from the historical data, and the probabilistic distributions of hourly wind generations would be prepared for the stochastic model as follows.

2.1 Probabilistic distributions of hourly wind generations

The historical wind power data collected from [34] in 2013 and 2014 are used to analyze the stochastic features of hourly wind generations. Daily wind power data in the same hour of a day over multiple years are assembled to estimate the parameters of probabilistic hourly wind generation curves. Taking the first hour as an example, all the wind generations in the hour 00:00 to 1:00 of each day during 2013 and 2014 were aggregated to estimate the wind generation probabilistic distribution at hour 1. Since the wind farm installation capacity was occasionally changed during these two years, wind generations were divided by its installation capacity and the normalized value was used to derive the probabilistic distribution as the histogram depicted in Fig. 1. It can be seen that the probability density curve for wind power $p_{w,t}$ during hour 00:00 to 1:00 could be well-fitted by a Weibull distribution with shape parameter λ=0.307 and scale parameter k=1.230 in (1). Likewise, the probabilistic wind generation models for the rest 23 hours from 1:00:00 to 24:00 could be derived from the corresponding historical data. It was found that they also observe the Weibull distributions with parameters detailed in Table 1.

$$f(p_{w,t},\lambda,k)=\frac{k}{\lambda}(\frac{p_{w,t}}{\lambda})^{k-1}e^{-(\frac{p_{w,t}}{\lambda})^{k}} \tag{1}$$

Based on the above analysis process for hourly wind generations, a total number of 24 Weibull distributions were strictly derived from wind generation historical data in [34] for the stochastic cost-benefit model proposed later. Though Weibull distributions were derived here, other probabilistic distributions of hourly wind generations could be similarly established from the corresponding historical generation data. With these 24 hourly-basis probabilistic distributions, the stochastic characteristics of wind generations during multiple years shall have been properly represented and they are ready to be incorporated in the stochastic model in the following section.

2.2 Stochastic cost-benefit model for optimal sizing of ESS

For the proposed stochastic cost-benefit model of ESS with uncertain wind generations, only the temporal arbitrage of ESS is considered in Unit Commitment (UC) for simplicity to determine ESS optimal size. However, the proposed stochastic model could be further extended as security constrained UC to take into account both the temporal and spatial arbitrages for obtaining the ESS size and locations in subsequent works.

The optimal size of ESS, characterized by its rated power and capacity (denoted as ${P_{ES}}^{Rated}$ and ${SOC_{ES}}^{installed}$ here) shall be figured out by energy-scheduling over the entire planning period to justify ESS costs by its benefits. However, solving such long-term energy-scheduling problem over multiple years is computationally cumbersome or even impractical. Instead, in this paper, with the amortized daily capital cost of ESS and the probabilistic distributions of hourly wind generations estimated in Section 2.1, an equivalent daily UC-based stochastic model is formulated as follows.

Assuming that ESS is owned by a Genco, the aim is to minimize the sum of generation fuel cost and ESS capital from the Genco's viewpoint. As wind generation at each hour is probabilistic, the generation fuel cost resulted from the corresponding UC solution will also be stochastic; thus a mixed objective function (2) including the generation fuel cost expectation plus the amortized daily ESS investment cost is designed as the objective of the proposed model

$$\text{Min } E(FC_{\cos t}) + P_{ES}^{Rated} \cdot IC_p + SOC_{ES}^{installed} \cdot IC_{soc} \tag{2}$$

where E stands for mathematical expectation calculation. In the first term, $FC_{\cos t}$ is the system fuel cost consisting of electricity generation cost, start-up cost and shut down cost of all generators over all time periods as (3)

$$FC_{\cos t} = \sum_{t=1}^{T} \sum_{i=1}^{N} [F(P_{it}) \cdot x_{it} + S_{Ui} \cdot x_{it} \cdot (1 - x_{i(t-1)}) + S_{Di} \cdot x_{i(t-1)} \cdot (1 - x_{it})] \tag{3}$$

where $F(P_{it}) = a_i \cdot (P_{it})^2 + b_i \cdot P_{it} + c_i$; a_i, b_i , and c_i are fuel cost coefficients of unit i, P_{it} is generation output of unit i at hour t.

The rated power of an ESS, constrained by the power converters, determines the maximum charging or discharging capability to support instantaneous power balance, whereas the rated capacity of an ESS, constrained by the storage volume, reflects the energy shifting capability. The rated power and capacity are two key physical parameters for ESS performance and its capital cost evaluation [28]. Therefore, the second and third terms in (2) stand for these capital costs which is generally proportional to each of these two parameters [28], and the cost coefficients are amortized from the one-time installation cost, annual operation and maintenance cost as (4) and (5).

$$IC_p = Inv_p \cdot \frac{r(1+r)^l}{(1+r)^l - 1} \cdot \frac{1}{N_{days}} \tag{4}$$

$$IC_{soc} = Inv_c \cdot \frac{r(1+r)^l}{(1+r)^l - 1} \cdot \frac{1}{N_{days}} + OM_c \cdot \frac{1}{N_{days}} \tag{5}$$

where Inv_c and Inv_p are the one-off installation cost per MWh and MW, OM_c is the ESS operation and maintenance cost per MWh-year; l is the ESS lifetime in years, r is the interest rate and N_{days} is the number of days in a year.

The proposed stochastic cost-benefit model for ESS size determination includes constraints of both conventional generators and ESS as follows.

1) System active power balance constraints

$$\sum_{i=1}^{N} P_{it} \cdot x_{it} + P_{w,t} + P_{dis,t} \cdot \eta_{dis} - P_{ch,t} / \eta_{ch} = P_{D,t} \tag{6}$$

2) Up and down spinning reserve constraints

$$\sum_{i=1}^{N} (P_{i,\max} - P_{it}) \cdot x_{it} + P_{ES}^{rated} \cdot \eta_{dis} - u_{dis,t} \cdot P_{dis,t} \cdot \eta_{dis} + u_{ch,t} \cdot P_{ch,t} / \eta_{ch} \geq= SR_{U,t} \tag{7}$$

$$\sum_{i=1}^{N} (P_{it} - P_{i,\min}) \cdot x_{it} + P_{ES}^{rated} / \eta_{ch} + u_{dis,t} \cdot P_{dis,t} \cdot \eta_{dis} - u_{ch,t} \cdot P_{ch,t} / \eta_{ch} \geq= SR_{D,t} \tag{8}$$

3) Unit ramping up and ramping down limits

$$P_{it} - P_{i(t-1)} \leq [1 - x_{it} \cdot (1 - x_{i(t-1)})] \cdot UR_i + x_{it} \cdot (1 - x_{i(t-1)}) \cdot P_{i,\min} \tag{9}$$

$$P_{i(t-1)} - P_{it} \leq [1 - x_{i(t-1)} \cdot (1 - x_{it})] \cdot DR_i + x_{i(t-1)} \cdot (1 - x_{it}) \cdot P_{i,\min} \tag{10}$$

4) Unit generation limits

$$P_{i,\min} \cdot x_{it} \leq P_{it} \leq P_{i,\max} \cdot x_{it} \tag{11}$$

5) Unit minimum ON/OFF time limits

$$(T_{i(t-1)}^{on} - MUT_i)(x_{i(t-1)} - x_{it}) \geq 0 \tag{12}$$

$$(T_{i(t-1)}^{off} - MDT_i)(x_{it} - x_{i(t-1)}) \geq 0 \tag{13}$$

Besides the above constraints of traditional generators, the constraints of ESS could be described as follows.

6) ESS charging and discharging power limits

$$0 \leq P_{ch,t} \leq u_{ch,t} \cdot P_{ES}^{Rated} \tag{14}$$

$$0 \leq P_{dis,t} \leq u_{dis,t} \cdot P_{ES}^{Rated} \tag{15}$$

7) Coupling constraints for ESS charging and discharging state variables

$$u_{ch,t} + u_{dis,t} \leq 1 \tag{16}$$

8) ESS State Of Charge (SOC) energy constraints at time *t*

$$SOC_t = SOC_{(t-1)} + P_{ch,t} \cdot \Delta t - P_{dis,t} \cdot \Delta t \tag{17}$$

$$\eta_1 \cdot SOC_{ES}^{installed} \leq SOC_t \leq \eta_2 \cdot SOC_{ES}^{installed} \tag{18}$$

9) ESS SOC energy at the end of each day shall be ready for continuous utilizations in the next day

$$SOC_T = SOC_0 \tag{19}$$

where P_{it} generation output of unit *i* at time *t*

$P_{i,max}$ maximum generation output of unit *i*

$P_{i.min}$ minimum generation output of unit *i*

x_{it} on/off status of unit *i* at time *t*

S_{Ui} startup cost of unit *i*

S_{Di} shutdown cost of unit *i*

$SOC_{ES}^{installed}$ ESS installed capacity

IC_{SOC} daily investment cost \$/MWh related to ESS capacity

P_{ES}^{Rated} ESS rated power

IC_p daily investment cost \$/MW related to ESS power

$P_{w,t}$ wind power output at time *t*

η_{ch}, η_{dis} charging and discharging efficiencies of ESS

η_1, η_2	lower and upper limit coefficients of ESS energy capacity
$P_{ch,t}$, $P_{dis,t}$	charging and discharging power of ESS at time t
$P_{D,t}$	load demand at time t
$SR_{U,t}$	up spinning reserve requirement at time t
$SR_{D,t}$	down spinning reserve requirement at time t
UR_i	ramp-up rate limit of unit i
DR_i	ramp-down rate limit of unit i
MUT_i	minimum up time of unit i
MDT_i	minimum down time of unit i
T_{it}^{on}	on period of unit i at time t
T_{it}^{off}	off period of unit i at time t
$u_{ch,t}$	charging state variable of ESS, 1 for charge, otherwise 0
$u_{dis,t}$	discharging state variable of ESS, 1 for discharge, otherwise 0
SOC_t	ESS SOC Energy at time t

It is clear that the physical meaning of the proposed model is to minimize Genco's mixed cost which consists of both the daily fuel cost expectation and amortized daily ESS capital cost with conventional generators' and ESS' constraints. Compared with the rolling deterministic day-by-day optimization approach over multiple years in [33], the proposed stochastic model first summarizes the uncertain features of wind generations from their long-term historical data, and then directly takes into account these uncertainties, therefore the proposed model is more suitable and flexible for system planning coupled with long-term uncertain wind generations.

With wind generation uncertainties incorporated in the model, how to effectively handle uncertain generations $P_{w,t}$ in the constraint (6) and conduct the expectation calculation E in the objective (1) becomes a critical challenge. In the following section, a hybrid approach based on the Point Estimated method embedded into the branch and bound algorithm is presented to address this challenge.

3. METHODOLOGY

As an effective tool to address stochastic problems, the point estimated (PE) method solves these problems generally in three steps: 1) with information of the raw moments of input variables, a few sampling points with weighting factors are firstly concentrated from the probabilistic distributions of input variables with their original statistical information retained; 2) afterwards the deterministic analysis procedures are conducted for these sampling points to obtain the deterministic solutions; 3) finally the stochastic characteristics of concerned outputs, such as the expectations or standard variations, would be calculated based on these deterministic solutions and their coupled weighting factors [35]. Among different versions of PE method such as 2*m*, 2*m*+1 and 4*m*+1 PE, 2*m*+1 PE scheme was reported as the best one with not only satisfactory accuracy of results but also relatively low computational burden [36,37]. This paper would therefore adopt the 2*m*+1 PE scheme to deal with wind generation uncertainties in the proposed UC-based stochastic model.

In the proposed model, the wind generation at each hour is one uncertain variable, and a total number of T uncertain wind generations for T hours are denoted by a vector (p_{w1}, p_{w2},…, p_{wt} ,…, p_{wT}) here. According to the PE theory [36,37], a set of wind power profiles is generated for (p_{w1}, p_{w2},…, p_{wt} ,…, p_{wT}) as follows: the uncertain wind power p_{wt} at hour t (t=1,2,…,T) is replaced with three locations $p_{wt,k}$ (k=1, 2, 3), while the remaining T-1 random wind powers are fixed at their mean values μ_{w1}, μ_{w2},…, μ_{wT}. Therefore, three wind power profiles, referred as concentrations of PE, would been produced as (μ_{w1} , μ_{w2},… $p_{wt,k}$,…, μ_{wT}) (k=1,2,3) for one wind generation p_{wt} at hour t (t=1,2,…,T). In other words, there are totally 3T concentrations representing the random wind power generations in a period of T hours. In detail, for probabilistic wind power p_{wt} at hour t, its three locations $p_{wt,k}$ are determined as

$$p_{wt,k} = \mu_{wt} + \varepsilon_{t,k} \cdot \sigma_{wt} \quad k = 1,2,3; t = 1,2,\dots T \tag{20}$$

where $\varepsilon_{t,k}$ is the standard location, μ_{wt} and σ_{wt} are the mean and standard deviation of the stochastic hourly-basis wind power at hour t, which could be easily calculated from its probability distribution function [36,37]. The standard location $\varepsilon_{t,k}$ and weight $\omega_{t,k}$ are furtherly calculated by the Hong's technique as follows.

$$\begin{cases} \varepsilon_{t,k} = \dfrac{\lambda_{t,3}}{2} + (-1)^{3-k}\sqrt{\lambda_{t,4} - \dfrac{3\lambda_{t,3}^2}{4}} & k = 1,2 \\ \omega_{t,k} = \dfrac{(-1)^{3-k}}{\varepsilon_{t,k}(\varepsilon_{t,1} - \varepsilon_{t,2})} & k = 1,2 \end{cases} \tag{21}$$

$$\begin{cases} \varepsilon_{t,3} = 0 & k = 3 \\ \omega_{t,3} = \dfrac{1}{T} - \dfrac{1}{\lambda_{t,4} - \lambda_{t,3}^2} & k = 3 \end{cases} \tag{22}$$

where $\lambda_{t,3}$ and $\lambda_{t,4}$ are the skewness and kurtosis of stochastic wind power p_{wt} at hour t. In (22), as the setting $\varepsilon_{t,3}$=0 yields $p_{wt,k} = \mu_{wt}$ in (20), T concentrations are the same as ($\mu_{w1}, \mu_{w2}, \ldots, \mu_{wt}, \ldots, \mu_{wT}$), and their weights would be added up as (23) for the concentration ($\mu_{w1}, \mu_{w2}, \ldots, \mu_{wt}, \ldots, \mu_{wT}$)

$$\omega_{2T+1} = \sum_{t=1}^{T} \omega_{t,3} = 1 - \sum_{t=1}^{T} \left(\frac{1}{\lambda_{t,4} - \lambda_{t,3}^2}\right) \tag{23}$$

thus the total number of 3T concentrations is reduced to 2T+1.

In the proposed stochastic model, each concentration ($\mu_{w1}, \mu_{w2}, \ldots p_{wt,k}, \ldots, \mu_{wT}$) ($t$=1,2,…,$T$) is a deterministic profile with T hourly wind generations, which would be used for the conventional UC scheduling to calculate the generation outputs and the fuel cost in (3). Here, marked the generation fuel cost of UC solution for the concentration ($\mu_{w1}, \mu_{w2}, \ldots p_{wt,k}, \ldots, \mu_{wT}$) as

$$FC_{t,k} = f(\mu_{w1}, \mu_{w2}, \ldots, p_{wt,k}, \ldots, \mu_{wT}) \tag{24}$$

For all the 2T+1concentrations, the deterministic UC problem would be addressed 2T+1 times to evaluate the fuel cost at each concentration. If denoted $FC_{t,k}$ as FC^s and the corresponding weighting factors $\omega_{t,k}$ as ζ_s (s=1, 2, …, 2T+1), the generation fuel cost expectation in (2) would be calculated as

$$E(FC_{\cos t}) = \sum_{s=1}^{2T+1} \zeta_s \cdot FC^s \tag{25}$$

Substitute (25) into (2) with the specific expression for FC^s, the objective of proposed stochastic model is established to minimize a mixed total cost expectation as (26)

$$\text{Min} \sum_{s=1}^{2T+1} \zeta_s \cdot \{\sum_{t=1}^{T}\sum_{i=1}^{N}[F(P_{it}^s) \cdot x_{it}^s + S_{Ui} \cdot x_{it}^s \cdot (1 - x_{i(t-1)}^s) + S_{Di} \cdot x_{i(t-1)}^s \cdot (1 - x_{it}^s)]\}$$

$$+SOC_{ES}^{installed}\cdot IC_{soc}+P_{ES}^{Rated}\cdot IC_{p} \tag{26}$$

where $F(P_{it}^{s})=a_i\cdot(P_{it}^{s})^2+b_i\cdot P_{it}^{s}+c_i$, x_{it}^{s} and P_{it}^{s} are on/off status and generation output variables of unit *i* at time *t* for the concentration *s*.

Following the same procedures, with the uncertain wind generations substituted by the concentrations generated by the PE strategy, the original constraints (6)-(19) could be transformed into a set of constraints (A1)-(A14) shown in the appendix of this paper.

As a whole, by using the PE strategy, the original stochastic cost-benefit model (1)-(19) has already been converted into a set of deterministic optimization problems consisting the objective (26) and constraints (A1)-(A14). These problems could be solved as a deterministic mix-integer nonlinear programming (MINLP) problem using many well-developed algorithms such as the branch and bound (BB) algorithm [38,39]. It is noted that this ESS sizing problem involves a significant number of control variables. For example, considering a 24-hour scheduling horizon with 10 generators, the number of variables would be (2×24+1)×10×4×24 for generators with (2×24+1)×5×24 variables for ESS. Consequently, such large-scale dimensional ESS optimal sizing problem could be too time-consuming to be directly solved by the BB method. However, since the constraints for each concentration *s* (s=1,2,…,2T+1) are only coupled by the ESS sizing variables P_{ES}^{Rated} and $SOC_{ES}^{installed}$ in equation (26), (A2)-(A3), (A9)-(A10) and (A13), this large-scale MINLP problem can be decoupled into 2T+1 smaller scale UC problems and readily solved in parallel for the given P_{ES}^{Rated} and $SOC_{ES}^{installed}$ values. A divide and conquer approach is therefore adopted to efficiently address this problem with the overall flowchart shown in Fig.2. The steps are generally depicted as follows.

1) Firstly, set the ESS rated power P_{ES}^{Rated} and capacity $SOC_{ES}^{installed}$ as discrete values within the allowable range. Each discrete pair of P_{ES}^{Rated} and $SOC_{ES}^{installed}$, denoted as (P_{ES}^{Rated}, $SOC_{ES}^{installed}$), would resemble a point in the mesh-grid;

2) Then, for each (P_{ES}^{Rated}, $SOC_{ES}^{installed}$) pair, 2T+1 deterministic UC problems corresponding to the 2T+1 concentrations generated by the PE strategy will be solved in parallel by the BB method to obtain the fuel cost FC^{s} (s=1, 2 ,…, 2T+1);

3) Afterwards, calculate the generation fuel cost expectation based on FC^{s}(s=1, 2 ,…,

$2T$+1) with weighting factors ζ_s (s=1, 2 ,…, $2T$+1) by (25), and further add the ESS capital cost according to (26) to obtain the system total cost for ESS size at (P_{ES}^{Rated}, $SOC_{ES}^{installed}$).

4) Repeat step *2)* to *3)* to calculate the system total cost by (26) for each pair (P_{ES}^{Rated}, $SOC_{ES}^{installed}$);

5) The pair (P_{ES}^{Rated}, $SOC_{ES}^{installed}$) with the minimum system total cost is the final solution of the planning problem as the ESS optimal size.

REMARKS:

1) The proposed solution approach using PE strategy to sample one set of typical concentrations to replace the original probabilistic wind generations is able to transform a complicated stochastic model into a deterministic optimization problem, which is much easier to be solved by many well-developed optimization algorithms. This is the rationale behind the proposed solution approach.

2) For the proposed UC-based stochastic model with uncertain wind generations for T hours, a total number of $2T$+1 deterministic optimizations are solved for calculating the objective in (2). This means that the computational burden of proposed solution approach is closely related to the length of scheduling horizon T considered in the UC problem while it is not sensitive to the amount of wind generation data to be taken into account in the planning problem, compared to the rolling day-by-day optimizations for multiple years in [33].

3) At the core of the proposed solution approach is the PE method which transforms the original probabilistic optimization problem into a deterministic one afterwards addressed by deterministic optimization algorithms. As there are no limitations for PE method to handle different probabilistic distributions, the proposed solution approach is generally applicable to the power system planning problems with various probabilistic distributions of wind generations and other typical uncertain renewable generations.

4. CASE STUDY

Two power system cases with 10 and 26 generating units are used here to test the proposed model. Four typical battery ESSs, namely Lead Acid Battery ESS (LAB-ESS), Advanced Battery Zn/Br ESS (AB Zn/Br-ESS), Advanced Battery Na/S ESS (AB Na/S-ESS), and Superconducting Magnetic ESS (SM-ESS) with parameters detailed in Table 2 [40]， are investigated in the 10-unit and 26-unit systems. The investment interest rate for all ESSs is 5%, and the ESS SOC energy is constrained between 10% and 90% of ESS installed capacity $SOC_{ES}^{installed}$. The ESS rated power and capacity are set as discrete values with a step of 10MW for P_{ES}^{Rated} in the range [0MW, 80MW] and a step of 10MWh for $SOC_{ES}^{installed}$ in the range [0MWh,80MWh]. The BB algorithm embedded in CPLEX optimization tool [41] is adopted as the optimization engine to solve the proposed model. The program is coded in Matlab 2011b and executed on a notebook with a 2.7GHz Intel Core i7-4600 CPU and 8GB RAM, and a computation platform with 4 local workers was built by Parallel Computing Toolbox 5.2 for running the parallel BB algorithm.

Benchmark Approach

The three-stage rolling approach to fix ESS sizing and siting for alleviating transmission network congestions in [33] is slightly modified as the benchmark for testing the stochastic model. Since the first stage in [33] is particularly designed to determine ESS locations for a congestion problem, only the second and third stages in [33] are extracted as the benchmark for determining optimal ESS size, which are generally described as follows.

1) A conventional UC problem without constraints on ESS power and capacity ratings is solved day-by-day for multiple years; afterwards with these UC solutions, the maximum charged or discharged power and the daily maximum energy stored are deemed as ESS power rating and capacity rating for each day. These daily power and capacity ratings of ESS are averaged over the whole multiple years and the averaged value is deemed as ESS size (P_{ES}^{Rated}, $SOC_{ES}^{installed}$).
2) Afterwards the UC problem is again solved day-by-day for multiple years to evaluate the cost-benefits, but this time with ESS constraints on ESS size (P_{ES}^{Rated}, $SOC_{ES}^{installed}$) obtained in step 1).

4.1 Case A: 10-unit system with Weibull distributions for hourly wind generations

A 10-unit system [42] was modified with uncertain wind generations as the first testbed for the proposed model. The wind farm was assumed with a rated power 300MW, and the hourly wind generations were modelled as a series of Weibull distributions with normalized parameters estimated in Table 1 together with 24-hour load demands. The lifetime of ESSs was assumed as 15 years with charging/discharging efficiency as 0.9. The up and down spinning reserve requirements of the system were set as eight percent of the load demands in each hour, while traditional generator parameters are given in Table 3 with startup and shutdown cost assumed as constant and zero, respectively.

With no ESS installed, the system total cost, which is equal to the fuel cost expectation in this condition, amounts to \$4495641.6 as shown in Table 4. With LAB-ESS installed, the proposed solution approach took 943s to find the optimal ESS size as P_{ES}^{Rated} =20 MW and $SOC_{ES}^{installed}$= 50 MWh with fuel cost expectation \$4491714.6. It can be seen that the 20MW/50MWh LAB-ESS leads to a \$3927 saving in generation fuel cost, which can offset the \$3188.7 LAB-ESS investment cost, resulting in a net system total cost saving of \$738.3.

Fig. 3 also plots the change of total cost expectation at different LAB-ESS rated power and energy capacity. As indicated by point A (P_{ES}^{Rated}=0MW, $SOC_{ES}^{installed}$=0MWh), the total fuel cost \$4495641.6 is quite high. With growing LAB-ESS rated power and capacity, the system total cost expectation reduces accordingly and reaches the minimum \$4494903.3 at the point B where P_{EV}^{Rated} =20MW, $SOC_{EV}^{installed}$=50MWh. If either the LAB-ESS rated power or capacity is increased further, the system total fuel cost expectation will increase again. Therefore, the best size of the LAB-ESS for the tested 10-unit system shall be 20MW rated power and 50MWh energy capacity for this system.

When the benchmark approach with rolling day-by-day optimizations in [33] was used to search the optimal ESS size for this system, it took 1584s to obtain a solution (P_{ES}^{Rated}=21.2MW, $SOC_{ES}^{installed}$=53.3MWh) with a system total cost as \$4489180.5 as shown in Table 5. Compared with the proposed stochastic model, their results are comparable while the proposed model is more computationally efficient. This is due to following reasons. The benchmark approach first conducted day-by-day optimizations in two years for minimizing the system cost and the final ESS optimal size was obtained as the average of these daily-optimized ESS size. The benchmark approach is equivalent to minimizing the average cost over two years in a series of day-by-day rolling optimal operations. While with regard to the stochastic model proposed in this paper, the model is designed to directly minimize the expected fuel cost by calculating the mathematical expectation in the objective (2). Since the approach in [33] and the one proposed in this paper have the similar physical meaning to optimize ESS size by minimizing system average cost, their solutions are therefore comparable. However, there are differences existing in the model formulations and solution processes of these two approaches. The proposed approach firstly derived the probabilistic features of wind generations based on two years' historical data, then directly considered these features in the stochastic model to minimize the average cost by using PE strategy and parallel BB algorithm. While the benchmark approach did not summarize the features of the wind generations, but utilized day-by-day rolling optimizations for multiple years and finally average the whole results as the ESS optimal size. Thus, the approach in [33] is an indirect scheme for determining the optimal size of ESS in a sense. It is also clear that with wind generation data accumulated for more years, the proposed stochastic model would be more flexible and applicable to system planning with long-term wind generations, as the probabilistic models of wind generations could still be readily derived from the long-term generation data firstly, and then directly used in the model without any additional efforts. However, the benchmark approach with day-by-day rolling optimizations would have to conduct a large and increasing number of deterministic optimization processes for the system planning with long-term wind generations.

The cost-benefit analysis is also applied to the AB Zn/Br-ESS. As shown in Fig. 4, the lowest total cost of the system is $4495641.6 with both rated power and capacity at zero, which means it is not economical to install any AB Zn/Br-ESS in this system. The optimal sizes of the rest two types of ESSs are also calculated and shown in Table 4. A total cost of $4495293.6 and $4495506.1 are incurred for the systems equipped with AB Na/S-ESS and SM-ESS, respectively, while $348 and $135.5 cost reduction per day are achieved compared with the system without ESS. Among the four types of ESSs, as the amortized daily capital cost of LAB-ESS is the lowest one with 59.39 \$/MW for power and 40.02 \$/MWh for capacity, the LAB-ESS shows the best economy for the 10-unit system with the optimal rated power and capacity at 20MW and 50MWh. From these comparisons, it is evident that the amortized daily cost of ESS is a key factor affecting the optimal size of ESS, and a battery with lower amortized daily cost would be the best choice for building ESS. Meanwhile, according to (4) and (5), the amortized daily cost could be reduced by decreasing the power-related and energy-rated cost, which would be achieved by adopting advanced battery materials, or cutting down the OM cost with improved ESS management.

To further investigate the impacts of ESS charging/discharging efficiency on system total cost, the LAB-ESS parameters η_{ch} and η_{dis} are varied from 1 to 0.8, and the resultant total cost expectations are plotted in Fig. 5. It shows that when LAB-ESS efficiency is higher than 0.80, the system total cost could be reduced by installing properly sized LAB-ESS. However, for the charging/discharging efficiency lower than 0.80, the LAB-ESS capital cost would exceed system fuel cost saving and it is more economical for the 10-unit system without any size of LAB-ESS. This result indicated that the charging/discharging efficiency shall be higher than a certain threshold such that system total cost could be reduced by installing proper size of ESS.

Similarly, how the LAB-ESS lifetime would influence the system total cost is also studied and relevant results are demonstrated in Fig. 6. As shown in Fig. 6, the longer the lifecycle of ESS is, the more system cost saving can be achieved because the amortized daily investment cost of ESS would be reduced as ESS lifespan grows. These results implied that effective and periodic regular battery maintenance, which facilitates maintaining ESS healthy operation status and extending battery service life, could also create more profits for the system with ESS.

4.2 Case B: 26-unit system with Beta distributions for hourly wind generations

A 26-unit system with a 500MW wind farm is used as the second testbed to investigate the proposed model. The fuel cost coefficients of generators are given in Table 6, and the system up and down spinning reserve are set as five percent of load demands in each hour. To show the capability of proposed approach for handling various probabilistic wind generations, instead of adopting the Weibull distribution as in case A, the hourly wind generations during five years in this case are modeled as a series of Beta (α, β) distributions [43] with parameters normalized by the rated power 500MW given in Table 7. The four typical ESSs with the parameters in Table 2 are also adopted for this 26-unit system.

In case without any ESS, the 26-unit system has a daily fuel cost expectation of \$5954752.0 as shown in Table 8. When the system is equipped with LAB-ESS, an optimal solution (P_{ES}^{Rated}=40MW, $SOC_{ES}^{installed}$=70MWh) with the system total cost expectation of \$5950636.4 is obtained in 5312s by the proposed approach. Compared with system total cost without any ESS, system total cost with LAB-ESS is reduced by \$4115.6 per day. At the end of the LAB-ESS service life which is assumed as 15 years in this study, the cost saving of 26-unit system achieved by LAB-ESS is accumulated to \$22532910. It can be seen that the benefits resulted from installing ESS in this 26-unit system is quite impressive.

When the benchmark approach in [33] was used to determine the ESS optimal size of this 26-unit system with wind generations available for five years, it took 24711s to find an optimal solution as (P_{ES}^{Rated}=38.8MW, $SOC_{ES}^{installed}$=73.5MWh) with a system total cost expectation \$5949827.2 as shown in Table 5. Compared with the solution of the proposed approach \$5950636.4, the benchmark algorithm solution is slightly better due to the continuous P_{ES}^{Rated} and $SOC_{ES}^{installed}$ adopted in the benchmark. Nevertheless, the computational time needed by proposed approach is significantly less. This demonstrated that the proposed algorithm could obtain an effective solution with higher computational efficiency than the deterministic day-by-day optimizations in [33], at an expense of slightly increased cost. In the 26-unit system, the speed-up ratio of the stochastic approach and the benchmark approach is 24711s/5312s=4.65, while the ratio in the 10-unit system is 1584s/943s=1.68. It is evident that the speed-up ratio in 26-unit system is much higher. This is because in the 26-unit system there are five years' wind generations available while in 10-unit system only two years' wind generation data are assumed available. As a result, the benchmark approach needs to conduct much more day-by-day optimizations for 26-unit system than that for 10-unit system. The proposed approach, however, could easily overcome such difficulty by deriving the probabilistic characteristics from five years' wind generations and directly taking into account those features in ESS sizing process, thus the computational efficiency of proposed approach is insensitive to the amount of wind generation data available for the planning problem.

Similarly, other three typical ESSs are also investigated to evaluate their costs and benefits. In specific, for systems with AB Zn/Br-ESS, AB Na/S-ESS and SM-ESS, the system total expected costs are \$5953306.9, \$5952595.5 and \$5952779.4, respectively as shown in Table 8. Compared with the total cost expectation of the original system without any ESS, the costs were reduced by \$1445.1, \$2156.5 and \$1972.6 per day, respectively. Among these four typical ESS batteries, LAB-ESS is the most economical one. LAB-ESS as the best choice for both the 10-unit and 20-unit system indicated that a battery with a cheaper amortized daily capital cost is an economical candidate for implementing ESS in power systems with uncertain wind generations.

The impacts of LAB-ESS charging/discharging efficiency and lifetime on 26-unit system total cost were also presented in Table 9. As the charging/discharging efficiency η_{ch} /η_{dis} varied from 0.8 to 0.95, the system total cost expectations were reduced from \$5954752.0 to \$5947815.3. In particular, there is no LAB-ESS installed in the system for the efficiency of 0.8, and the 26-unit system has a very high total cost. As LAB-ESS lifetime increases from 5 years to 20 years, the system total cost decreases accordingly. These results indicated that high efficiency and longer service life of LAB-ESS could provide power systems with more benefits.

5. CONCLUSION

In this paper, with probabilistic distributions of hourly wind generations derived from historical data of multiple years, a general and flexible stochastic cost-benefit analysis model, which considered the generation fuel expected costs plus the ESS amortized daily capital costs, was proposed to directly determine the ESS optimal size for power system planning with uncertain wind generations. The stochastic model was ingeniously transformed into a deterministic one by using the Point Estimated method, and then efficiently solved by the proposed parallel BB optimization algorithm. Four types of ESSs with varied battery parameters were analyzed in two modified multiple-unit systems, and the impacts of ESS charging/discharging efficiency and lifetime on ESS cost-benefits were also fully investigated and discussed. The simulation results have demonstrated that the proposed stochastic cost-benefit model is effective to optimize ESS size in power system planning couple with intermittent wind generations.

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APPENDIX

The original constraints of the proposed stochastic model could be transformed into the following constraints by using PE method.

$$\sum_{i=1}^{N} P_{it}^{s} \cdot x_{it}^{s} + P_{w,t}^{s} + P_{dis,t}^{s} \cdot \eta_{dis} - P_{ch,t}^{s} / \eta_{ch} = P_{D,t} \tag{A1}$$

$$\sum_{i=1}^{N} (P_{i,\max} - P_{it}^{s}) \cdot x_{it}^{s} + P_{ES}^{rated} \cdot \eta_{dis} - u_{dis,t}^{s} \cdot P_{dis,t}^{s} \cdot \eta_{dis} + u_{ch,t}^{s} \cdot P_{ch,t}^{s} / \eta_{ch} \geq= SR_{U,t} \tag{A2}$$

$$\sum_{i=1}^{N} (P_{it}^{s} - P_{i,\min}) \cdot x_{it}^{s} + P_{ES}^{rated} / \eta_{ch} + u_{dis,t}^{s} \cdot P_{dis,t}^{s} \cdot \eta_{dis} - u_{ch,t}^{s} \cdot P_{ch,t}^{s} / \eta_{ch} \geq= SR_{D,t} \tag{A3}$$

$$P_{it}^{s} - P_{i(t-1)}^{s} \leq [1 - x_{it}^{s} \cdot (1 - x_{i(t-1)}^{s})] \cdot UR_{i} + x_{it}^{s} \cdot (1 - x_{i(t-1)}^{s}) \cdot P_{i,\min} \tag{A4}$$

$$P_{i(t-1)}^{s} - P_{it}^{s} \leq [1 - x_{i(t-1)}^{s} \cdot (1 - x_{it}^{s})] \cdot DR_{i} + x_{i(t-1)}^{s} \cdot (1 - x_{it}^{s}) \cdot P_{i,\min} \tag{A5}$$

$$P_{i,\min} \cdot x_{it}^{s} \leq P_{it}^{s} \leq P_{i,\max} \cdot x_{it}^{s} \tag{A6}$$

$$(T_{on,i(t-1)}^{s} - MUT_{i})(x_{i(t-1)}^{s} - x_{it}^{s}) \geq 0 \tag{A7}$$

$$(T_{off,i(t-1)}^{s} - MDT_{i})(x_{it}^{s} - x_{i(t-1)}^{s}) \geq 0 \tag{A8}$$

$$0 \le P_{ch,t}^{s} \le u_{ch,t}^{s} \cdot P_{ES}^{Rated} \quad \text{(A9)}$$

$$0 \le P_{dis,t}^{s} \le u_{dis,t}^{s} \cdot P_{ES}^{Rated} \quad \text{(A10)}$$

$$u_{ch,t}^{s} + u_{dis,t}^{s} \le 1 \quad \text{(A11)}$$

$$SOC_{t}^{s} = SOC_{t-1}^{s} + P_{ch,t}^{s} \cdot \Delta t - P_{dis,t}^{s} \cdot \Delta t \quad \text{(A12)}$$

$$\eta_1 \cdot SOC_{ES}^{installed} \le SOC_{t}^{s} \le \eta_2 \cdot SOC_{ES}^{installed} \quad \text{(A13)}$$

$$SOC_{0}^{s} = SOC_{T}^{s} \quad \text{(A14)}$$

where the variables with superscript *s* are the corresponding value for the concentration *s* generated by the PE method.

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Table 1 Hourly load demands and Weibull distributions of wind power in 10-unit system

Hour	Load demand (MW)	Normalized Weibull distributions of p_{wt}		Hour	Load demand (MW)	Normalized Weibull distributions of p_{wt}	
		λ	k			λ	k
1	700	0.307	1.230	13	1400	0.261	1.027
2	750	0.305	1.226	14	1300	0.265	1.028
3	850	0.299	1.210	15	1200	0.270	1.040
4	950	0.296	1.185	16	1050	0.277	1.064
5	1000	0.291	1.170	17	1000	0.280	1.063
6	1100	0.289	1.161	18	1100	0.289	1.083
7	1150	0.287	1.157	19	1200	0.297	1.105
8	1200	0.284	1.152	20	1400	0.303	1.146
9	1300	0.276	1.108	21	1300	0.306	1.178
10	1400	0.266	1.062	22	1100	0.311	1.202
11	1450	0.260	1.046	23	900	0.315	1.229
12	1500	0.257	1.019	24	800	0.313	1.248

Table 2 Key parameters of various ESSs

Parameters	LAB-ESS	AB Zn/Br-ESS	AB Na/S-ESS	SM-ESS
Energy-rated Inv_c ($/kWh)	150	400	250	500
Power-rated Inv_p ($/kW)	225	175	150	300
OM-rated OM_c ($/MW-year)	155	100	100	100
Efficiency $\eta_{ch}=\eta_{dis}$	0.90	0.85	0.85	0.92
Lifetime l(year)	15	20	20	30

Table 3 Conventional Generator data for 10-unit system

Unit	$P_{\max}$ (MW)	$P_{\min}$ (MW)	a (\$/MW^2 h)	b (\$/MWh)	c (\$/h)	MUT (h)	MDT (h)	S_U(\$)	S_D(\$)	Initial (h)
1	455	150	0.0048	161.9	1000	8	8	4500	0	8
2	455	150	0.0031	172.6	970	8	8	5000	0	8
3	130	20	0.0200	166.0	700	5	5	550	0	-5
4	130	20	0.0211	165.0	680	5	5	560	0	-5
5	162	25	0.0398	197.0	450	6	6	900	0	-6
6	80	20	0.0712	222.6	370	3	3	170	0	-3
7	85	25	0.0079	277.4	480	3	3	260	0	-3
8	55	10	0.0413	259.2	660	1	1	30	0	-1
9	55	10	0.0222	272.7	665	1	1	30	0	-1
10	55	10	0.0173	277.9	670	1	1	30	0	-1

Table 4 Cost comparisons for 10-unit system with and without ESS

ESS Type	Optimal Sizing		Fuel Cost Expectation (\$)	ESS Cost (\$)	Total Cost Expectation (\$)	Cost Saving (\$)
	P_{ES}^{Rated} (MW)	$SOC_{ES}^{installed}$ (MWh)				
No ESS	0	0	4495641.6	0	4495641.6	-
LAB-ESS	20	50	4491714.6	3188.7	4494903.3	738.3
AB Zn/Br-ESS	0	0	4495641.6	0	4495641.6	0
AB Na/S-ESS	20	20	4493529.4	1764.2	4495293.6	348
SM-ESS	10	10	4494077.6	1428.5	4495506.1	135.5

Table 5 Comparisons of solution quality and time consuming for LAB-ESS

		optimal Sizing		Time (s)	Total Cost Expectation (\$)	Comparisons
		P(MW)	C(MWh)			
10-unit system	[33]	21.2	53.3	1584	4489180.5	Time ratio=1.68; Accuracy =99.9%
	Proposed	20	50	943	4494903.3	
26-unit system	[33]	38.8	73.5	24711	5949827.2	Time ratio=4.65; Accuracy =99.9%
	Proposed	40	70	5312	5950636.4	

Table 6 Conventional Generator data of 26-unit system

Unit	$P_{\max}$ (MW)	$P_{\min}$ (MW)	a (\$/MW^2 h)	b (\$/MWh)	c (\$/h)	MUT (h)	MDT (h)	S_U(\$)	S_D(\$)	Initial (h)
1	400	100	0.019	75.031	311.9102	8	5	500	0	10
2	400	100	0.019	74.921	310.0021	8	5	500	0	10
3	350	140	0.015	108.616	177.0575	8	5	300	0	10
4	197	68.95	0.026	232	260.176	5	4	200	0	-4
5	197	68.95	0.026	231	259.649	5	4	200	0	-4
6	197	68.95	0.026	230	259.131	5	4	200	0	-4
7	155	54.25	0.049	107.583	143.5972	5	3	150	0	5
8	155	54.25	0.048	107.367	143.3719	5	3	150	0	5
9	155	54.25	0.047	107.154	143.0288	5	3	150	0	5
10	155	54.25	0.046	106.94	142.7348	5	3	150	0	5
11	100	25	0.06	182	218.7752	4	2	70	0	-3
12	100	25	0.061	181	218.335	4	2	70	0	-3
13	100	25	0.062	180	217.8952	4	2	70	0	-3
14	76	15.2	0.093	134.073	81.6259	3	2	50	0	3
15	76	15.2	0.091	133.805	81.4641	3	2	50	0	3
16	76	15.2	0.089	133.538	81.298	3	2	50	0	3
17	76	15.2	0.088	133.272	81.1364	3	2	50	0	3
18	20	4	0.143	378.896	118.8206	0	0	20	0	-1
19	20	4	0.136	377.77	118.4576	0	0	20	0	-1
20	20	4	0.126	376.637	118.1083	0	0	20	0	-1
21	20	4	0.12	375.51	117.7551	0	0	20	0	-1
22	12	2.4	0.285	260.611	24.8882	0	0	0	0	-1
23	12	2.4	0.284	259.318	24.7605	0	0	0	0	-1
24	12	2.4	0.28	258.027	24.6382	0	0	0	0	-1
25	12	2.4	0.265	256.753	24.411	0	0	0	0	-1
26	12	2.4	0.253	255.472	24.3891	0	0	0	0	-1

Table 7 Hourly load demands and Beta distributions for wind power in 26-unit system

Hour	Load demand (MW)	Normalized Beta distributions of p_{wt}		Hour	Load demand (MW)	Normalized Beta distributions of p_{wt}	
		α	β			α	β
1	2223	4.849	9.577	13	2565	3.986	1.673
2	2052	1.284	7.755	14	2508	1.827	4.718
3	1938	1.472	10.822	15	2479.5	6.83	8.197
4	1881	5.953	5.274	16	2479.5	6.378	1.692
5	1824	4.278	1.777	17	2593.5	5.772	6.304
6	1825.5	5.95	5.002	18	2850	2.833	7.37
7	1881	4.907	3.668	19	2821.5	2.91	9.958
8	1995	5.374	9.295	20	2764.5	6.943	11.753
9	2280	1.242	4.066	21	2679	6.621	7.342
10	2508	4.84	11.393	22	2662	1.993	9.944
11	2565	2.526	6.886	23	2479.5	6.618	9.199
12	2593.5	3.893	8.94	24	2308.5	7.161	10.032

Table 8 Cost comparisons for 26-unit system with and without ESS

ESS Type	Optimal Sizing		Fuel Cost Expectation ($)	ESS Cost ($)	Total Cost Expectation ($)	Cost Saving ($)
	P_{ES}^{Rated} (MW)	$SOC_{ES}^{installed}$ (MWh)				
No ESS	0	0	5954752.0	0	5954752.0	-
LAB-ESS	40	70	5945459.6	5176.8	5950636.4	4115.6
AB Zn/Br-ESS	10	10	5952040.1	1266.8	5953306.9	1445.1
AB Na/S-ESS	30	40	5949396.8	3198.7	5952595.5	2156.5
SM-ESS	20	20	5949922.4	2857.0	5952779.4	1972.6

Table 9 Impacts of LAB-ESS parameters on 26-unit system total cost expectation

LAB-ESS parameters		Total Cost Expectation ($)
Lifetime=15 years	charging/discharging Efficiency=0.80	5954752.0
	0.85	5953127.1
	0.90	5950636.4
	0.95	5947815.3
Charging/discharging efficiency=0.90	Lifetime=5 years	5954752.0
	10 years	5952632.6
	15 years	5950636.4
	20 years	5949000.9

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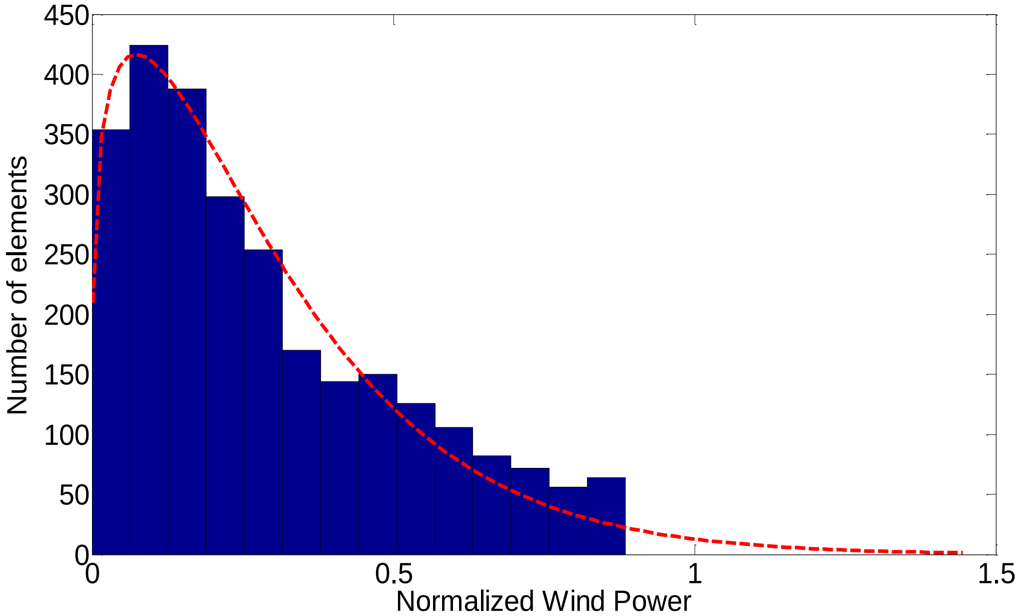
Fig. 6 Total cost expectation vs. LAB-ESS lifetime for 10-unit system



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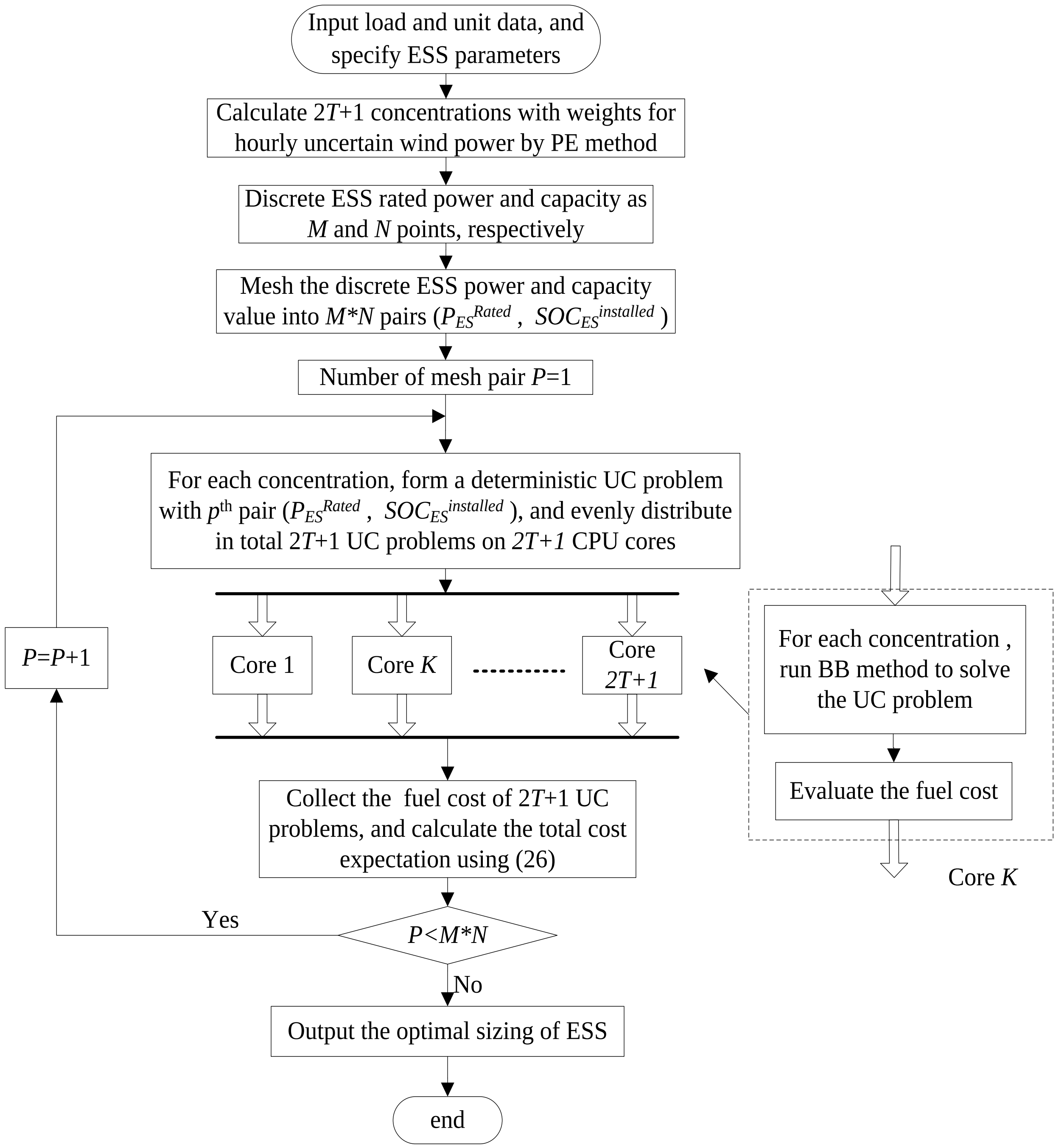

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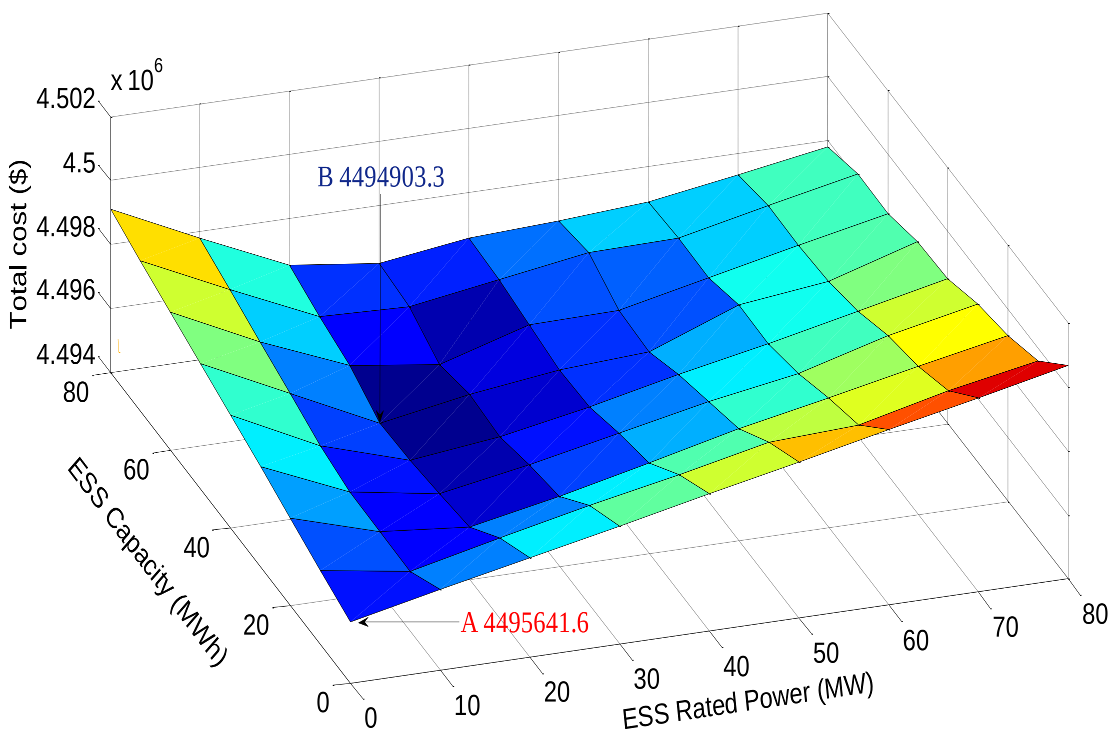

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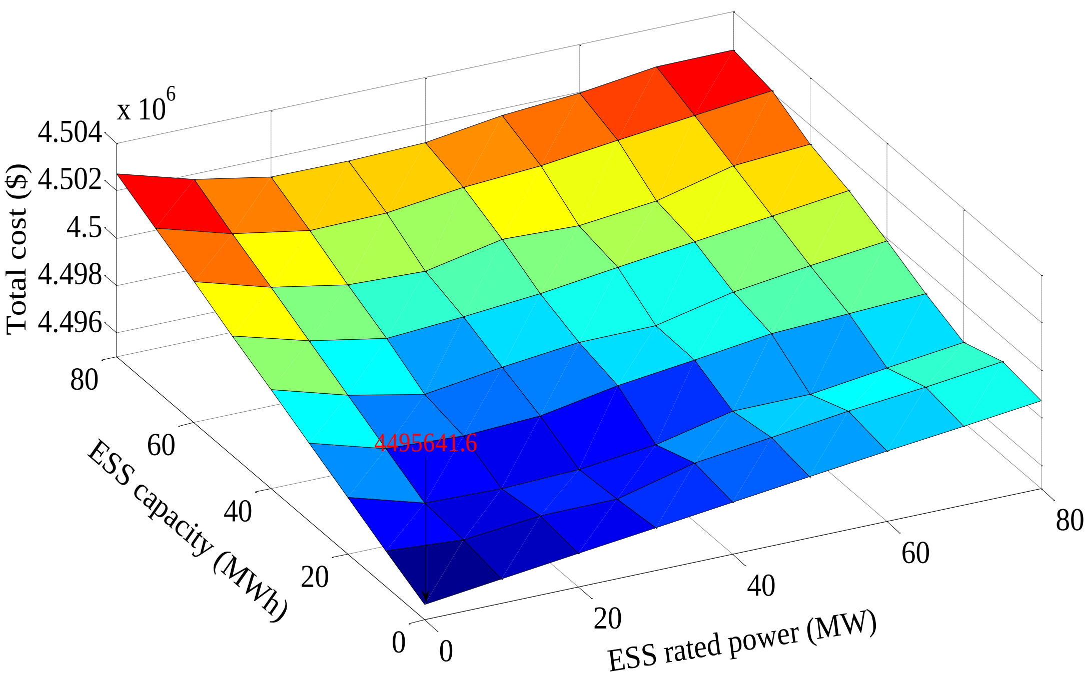

Fig. 4 Optimal size of AB Zn/Br-ESS for 10-unit system

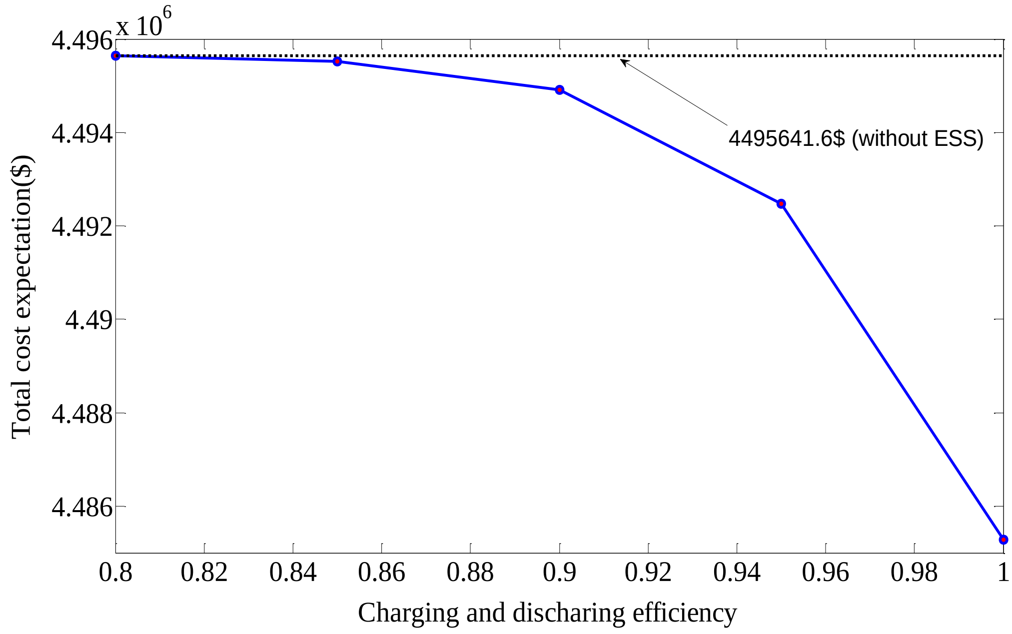

Fig. 5 Total cost expectation vs. LAB-ESS charging/discharging efficiency for 10-unit system

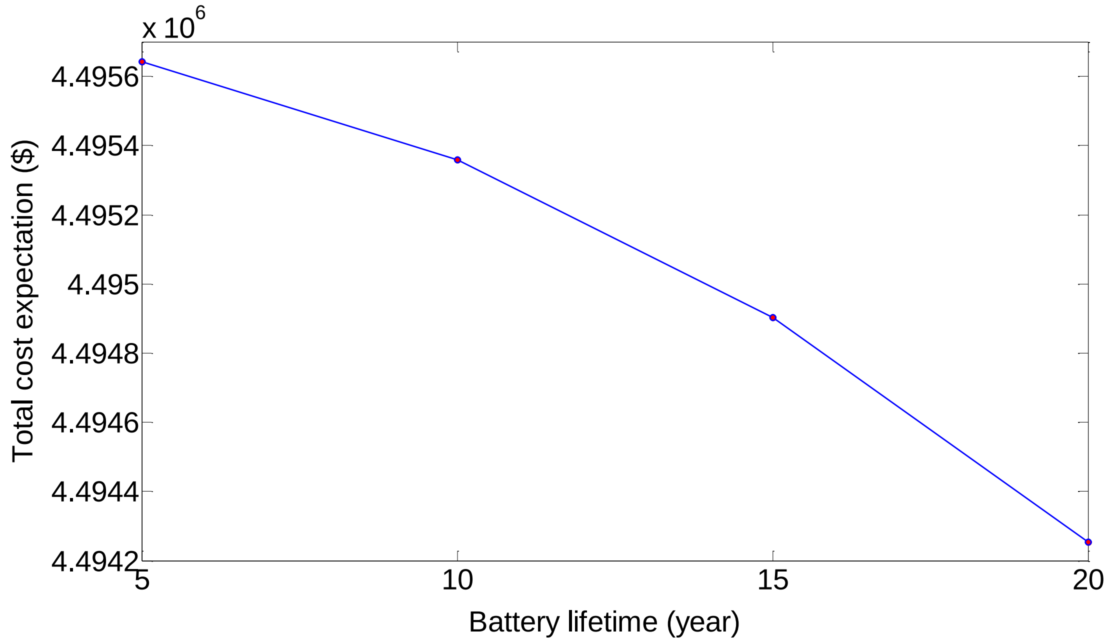

Fig. 6 Total cost expectation vs. LAB-ESS lifetime for 10-unit system