Multi-Objective Chance Constrained Optimal Day-Ahead Scheduling Considering BESS Degradation

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***Abstract*—As battery technology matures, the battery energy storage system (BESS) becomes a promising candidate for addressing renewable energy uncertainties. The BESS degradation is one of key factors in BESS operation, which is usually considered in the planning stage. However, BESS degradations is directly affected by the depth of discharge (DoD), which is closely related to BESS daily schedule. Specifically, the BESS life losses may be different when providing the same amount of energy under distinct DoD. Therefore, it is necessary to develop a model to consider the effect of daily discharge on BESS degradation. In this paper, a model quantifying the nonlinear impact of DoD on BESS life loss is proposed. By adopting the chance constrained goal programming, the degradation in day-ahead unit commitment is formulated as a multi-objective optimization problem. To facilitate an efficient solution, the model is converted into a mixed integer linear programming problem. The effectiveness of the proposed method is verified in a modified IEEE 39-bus system.**

***Index Terms*—BESS degradation, Chance constraints, Depth of discharge.**

NOMENCLATURE

A. Indices, sets and parameters

i	Index of thermal units.
j	Index of the BESS
m	Index of wind farms.
n	Index of demands.
t	Index of time periods.
G	Set of thermal units.
E	Set of the BESS.
W	Set of wind farms.
D	Set of demands.
T	Set of time periods.
Δt	Time periods.
u^+/u^-	Penalty of the corresponding deviation.
k	Target value of the corresponding function.
$K_{q,j}$	Slope of qth segment of BESS j
β^{up}/β^{dn}	Confidence level for the upward/downward reserve.
$p_i^{g\max}/p_i^{g\min}$	Maximal/minimal power of unit i.
$p_j^{chg\max}/p_j^{dsg\min}$	Maximal charge/discharge power of BESS.
$c_j^{\max}/c_j^{\min}$	Maximal/minimal capacity of BESS.
η_j^c/η_j^d	Charge/discharge efficiency of BESS.
$p_{m,t}^w/p_{n,t}^d$	Forecast wind/load power.
$a_i/b_i/c_i$	Fuel cost parameter of unit.
su_i/sd_i	Startup/shutdown cost of unit.
$T_{on,i}/T_{off,i}$	Minimum on/ off time of unit.
ru_i/rd_i	Ramp up/ down limit of unit i.
$\sigma_{m,t}^w$	The standard deviation of forecasting errors of wind farm m during period t.
$p_m^{w\max}$	Maximal power of wind farm m.

B. Functions

$f_{LL}(\,)$	Life loss under corresponding DoD.
$\varphi(\,)$	Inverse cumulative distribution function of wind power.
$C_{op}(\,)$	Total operation cost.

C. Variables

$dod^{mi\%,mf\%}$	DoD from m_i% to m_f%.
$dod_{j,t}$	DoD of BESS j at time t.
d^+/d^-	Positive/negative deviation from the target value.
$\upsilon_{i,t}$	On/off status of unit.
$z_{i,t}^{su}/z_{i,t}^{sd}$	Startup/shutdown status of unit.
$\upsilon_{j,t}^{chg}/\upsilon_{j,t}^{dsg}$	Charge/discharge status of BESS.
$p_{i,t}^g$	Power output of unit.
$p_{j,t}^e$	Power output of BESS.
$p_{j,t}^{chg}/p_{j,t}^{dsg}$	Charge/discharge power of BESS.
$r_{i,t}^{g,up}/r_{i,t}^{g,dn}$	Upward/downward reserve of unit.
$r_{j,t}^{e,up}/r_{j,t}^{e,dn}$	Upward/downward reserve of BESS.
r_t^{up}/r_t^{dn}	Total upward/downward reserve.
$\lambda_{j,t}^{r,g}$	Reserve cost of unit.
$\lambda_{j,t}^{e}$	Output cost of the BESS.
$\lambda_{j,t}^{r,e}$	Reserve cost of the BESS.
$c_{j,t}$	Energy capacity of BESS.
$\tilde{p}_{m,t}^w$	Probabilistic forecast of wind power.
$t_{on,i,t}/t_{off,i,t}$	On/ off time of unit.

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$R_{q,j,t}$	Binary variable indicating whether constraint actives or not.
$LL^{mi\%,mf\%}$	Life loss from m_i% to m_f%.
$NLL^{mi\%,mf\%}$	Normalized life loss from m_i% to m_f%.

I. Introduction

With growing integration of renewable generations, their uncertainties and variations make it difficult for the system operator (SO) to make day-ahead schedules. To tackle these uncertainties and variations, SO calls for novel flexible resources [1]. Driven by the need to integrate renewable generations, the energy storage system (ESS) becomes a promising candidate for addressing system uncertainties and improving system operation efficiency.

ESSs can shift energy demand to when it is optimal to be consumed according to the decision makers' requirements, technical and economic characteristics of ESSs [2]-[7]. Among various kinds of ESSs, the battery ESS (BESS) is playing an important role in the future power systems. Several BESS applications in system operation have been studied to deploy their energy-shifting and fast-ramping, in primary frequency control [2]-[3], peak shaving [4], ramp capability [5], voltage control [6] and energy arbitrage [7].

For a specific BESS, the cost can be modeled on planning [8] and operation [2]-[7] stages, respectively. The planning models the relationship between BESS size and investment cost. For an integrated BESS, the operation models should capture the cost with respect to specific BESS scheduling. These scheduling generally includes day-ahead unit commitment [9], intra-day dispatch [10] and real-time operation [1]-[2], [4]. Because the BESS's capacity is limited, a multi-time step BESS operation model is preferred. Furthermore, day-ahead unit commitment is the cornerstone of economic operation in most power systems [11]. As a result, this paper pays attention on the BESS operation cost with respect to day-ahead scheduling plan, e.g. the period and amount of charging and discharging. However, to guarantee the operation efficiency of power system with BESSs integrated, an important concern is how long the BESS can operate in normal condition.

As one of the key factors, the degradation of BESS is affected by operating temperature, depth of discharge (DoD) and charging/discharging current rate and so on [12]. The BESS degradation models could be classified into theoretical models and empirical models [13]. Theoretical models usually focus on the degradation mechanism, i.e. how do different conditions affect BESS degradation [14]-[15]. They are often applied in the life cycle prediction of BESS. Comparatively, empirical models are often applied in the BESS planning and operating problem to quantify the life loss or the remaining cycle life [16]-[17], the majority of which are for planning problems. Reference [18] proposes a BESS allocation model and introduces the residual value to reflect the degradation of BESS. In [19], a robust optimization based storage investment model is proposed, and the investment cost is considered in planning. As for the daily operating models, the degradation model is usually formulated based on the simplified assumptions. For example, BESS maintenance cost is assumed to be linear to the power output of BESS in [20]. In [21]-[22], the BESS usage cost is treated proportional to the state of charge (SoC).

Different from thermal generations, the majority operational cost of BESS comes from its degradation cost. It is necessary to predict the BESS degradation under various operation scenarios. To some extents, BESS degradation cost is the embodiment of its investment cost. It is no doubt that the investment cost should be considered in planning stage. However, the life cycle of BESS, which is one of the indexes to quantify BESS degradation, can be only predicted on the basis of average in this stage. This life cycle is directly affected by the dispatching of BESS, which under different schedules may vary more than 50% [23]. Thus, it is of significance to consider the BESS degradation caused by charging and discharging in the daily dispatch model. Compared with the linear model [20]-[22], this relationship in [23] is more applicable to connect the technical and economic characteristic of BESS.

For the power system with mixed power sources and BESS, the SO should maximize the social welfare by optimally schedule different kinds of sources. When the relationship between BESS life loss and its scheduling plan is revealed, the SO should balance the operation costs of BESS and other sources, e.g. thermal generations. In addition, in many degradation models, the rain flow counting is applied to identify discharging cycles, which is often used in fatigue analyzing problem [24]-[25]. However, this technic introduces non-convex to the decision making problem, which is computationally demanded. As a result, a novel decision making model is needed for the SO to schedule the integrated BESSs in day-ahead unit commitment.

In order to effectively optimize the day ahead scheduling with the uncertain wind, several methods have been proposed, including robust UC [26], interval UC [27], stochastic UC [28], CCP based UC [29] and risk based UC [30]-[31]. Each of them has distinct advantages and disadvantages [32]. Among these methods, CCP is one of ways comprehensively considering the distribution information of uncertainties and efficiently modeling the UC problem. By introducing probabilistic constraints, CCP reduces the undue influence of extreme events, and takes the SO's risk preference into consideration. CCP based scheduling models are proposed to consider uncertain wind power and generator loss in [29] and [33], respectively. Apart from the reserve capacity, CCP is also applied to address transmission capacity constraints in [34]. As the improvement of CCP, reference [35] combines two stage programming and CCP to solve UC problem. A CCP based wind power range quantification approach is proposed to determine dynamic uncertainty intervals, in security constrained UC problem [36]. The general CCP based model only consider uncertainties in constraints, while [37] proposes the chance constrained goal programming (CCGP), considering uncertainties in both constraints and objectives. As a challenging problem, solving methods of CCP have been studied for decades, including p-level efficient points [38], optimality conditions [39], nonlinear programming [40] and deterministic reformulation [41].

In this paper, an optimal scheduling method for power system with BESS based on CCGP is proposed, in which the nonlinear effect of discharging on degradation is modeled without rain flow counting. With the help of CCGP, BESS degradation is considered as one of objectives in the model, meanwhile the uncertain renewable energy resource are addressed by chance constraints. The main contribution of this paper could be summarized as follows:

i). The CCGP method is introduced to model the day ahead scheduling problem as a multi-objective stochastic optimization problem, in which the operation cost, life loss of BESS and risk level of power systems with wind power integrated are simultaneously optimized.

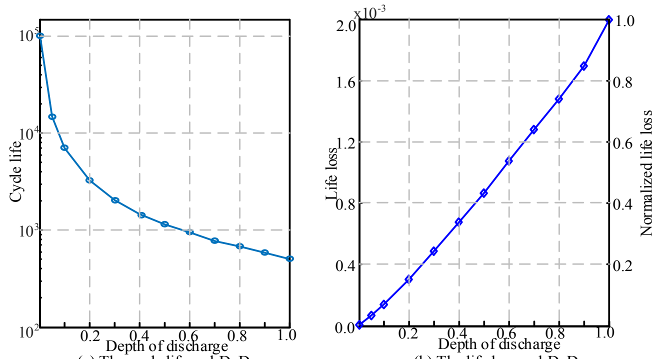
ii). It pointed out that the BESS degradation is closely related to its daily discharge plan. Thus, the BESS degradation should be well considered in the operating stage. The thermal generators and BESS should cooperate with each other in daily dispatching.

iii). The nonlinear characteristic of discharging on BESS life loss is modeled when optimizing schedules, which combines the scheduling of BESS and DoD into the life loss assessment of BESS. It also indicates that providing the same amount of energy may lead to different BESS degradations.

The rest of the paper is organized as follows: Section II introduces the effect of DoD on the loss of cycle life. Section III formulates the CCGP based optimal scheduling model with considering the BESS degradation. Section IV presents the model transformation and solution. Section V illustrates the numerical results of the proposed model, and Section VI provides conclusions of the paper.

II. The BESS Degradation

One of the critical factors affecting the life cycle of BESS is DoD, which is closely related to the day-ahead scheduling. The relationship between DoD and life loss of BESS is mainly focused in this paper. Several DoD stress models have been proposed on related topics, illustrating the life losses of BESS under some certain conditions. As for daily dispatching, the commonly used DoD stress model has some drawbacks as follows. i) Some models use linear functions to describe the effect of DoD, which are not consistent with the physical characteristics. ii) And some works make assumptions that the DoD only starts from 100% SoC, which is usually incorporated within the rain flow counting technique.



(a) The cycle life and DoD (b) The life loss and DoD

Fig.1 The degradation and DoD

Taking the lithium-ion battery as an example, Fig. 1(a) in [23] presents the cycle life under different DoDs. To more intuitively present the DoD effect on BESS life loss, Fig.1 (a) can be transferred into Fig. 1(b). It is shown that DoD has a nonlinear impact on the life loss, which indicates degradations may be different when providing the same amount of energy. And this nonlinear effect caused by dispatching should be formulated in the optimal scheduling model to optimally reduce the life loss of BESS. Meanwhile, the life loss is not only decided by the relative deviation of DoDs, but also affected by the absolute (or average) DoD. Reference [42] uses a second order polynomial function to present the effects of DoD and the average SoC on the cycle life of BESS. Furthermore, [13] proposes that the rain flow counting can be only applied off-line over a recorded profile and it is not suitable for real-time evaluation. Thus, a more efficient method should be applied for the daily dispatch model.

In order to formulate the effects of both the relative and the absolute DoD, we start from the basic definition. According to [43], when there is one BESS discharging from 100% to m_i% SoC, the life loss can be presented as (1). Similarly, the life loss caused by the discharge from 100% to m_f% SoC can be presented as (2). ($m_i\%>m_f\%$)

$$LL^{100\%,m_i\%}=f_{LL}\left(dod^{100\%,m_i\%}\right) \tag{1a}$$

$$NLL^{100\%,m_i\%}=f_{LL}\left(dod^{100\%,m_i\%}\right)/f_{LL}\left(dod^{\max,\min}\right) \tag{1b}$$

$$LL^{100\%,m_f\%}=f_{LL}\left(dod^{100\%,m_f\%}\right) \tag{2a}$$

$$NLL^{100\%,m_f\%}=f_{LL}\left(dod^{100\%,m_f\%}\right)/f_{LL}\left(dod^{\max,\min}\right) \tag{2b}$$

Essentially, the process of discharge from 100% to m_f% can be regarded as the discharge from 100% to m_i% and then from m_i% to m_f%, $m_i \geq m_f$. Thus, when there is a discharge from m_i% to m_f%, the corresponding life loss can be described as (3).

$$LL^{m_i\%,m_f\%}=LL^{100\%,m_f\%}-LL^{100\%,m_i\%},\ m_i\%\geq m_f\% \tag{3a}$$

$$NLL^{m_i\%,m_f\%}=NLL^{100\%,m_f\%}-NLL^{100\%,m_i\%},\ m_i\%\geq m_f\% \tag{3b}$$

$$NLL^{m_i\%,m_f\%}=\frac{f_{LL}\left(dod^{100\%,m_f\%}\right)-f_{LL}\left(dod^{100\%,m_i\%}\right)}{f_{LL}\left(dod^{\max,\min}\right)} \tag{3c}$$

Besides, (3b) can be expanded as (3c), by substituting (1) and (2). When the discharge starts from 100% SoC (m_i=100), then $f_{LL}(dod^{100\%,100\%})\approx 0$. It indicates that (3b) is also consistent with the basic definition (1b). According to Fig. 1(b), the life loss of the discharge from 10% to 0% is 2.29 times of the discharge from 100% to 90%, which indicates that the DoD conditions during the discharge process has a considerable influence on the life loss. Consequently, the same amount of discharge under different SoC has different impacts of life loss of BESS.

Note that in this paper the lithium-ion battery is used as an example to introduce the method, which is a promising candidate in the future. Although different batteries have different degradation models (curves shown in Fig.1), the similar idea could be applied in these studies.

III. CCGP Based Dispatching Model

A. Chance-Constrained Goal Programming

Chance Constrained Programming (CCP) [44] is one of the effective methods to address uncertain problems, in which the constraint can be violated within a predefined probability level. In other words, the probability of constraint to be met should be higher than the predefined confidence level. The general form of the chance constraint programming can be presented as (4), where x is a decision vector, ξ is a stochastic vector, $f_i(\ )$ is the ith function, with the corresponding risk level β_i and target value k_i.

$$\Pr\left\{f_i\left(x,\xi\right)\le k_i\right\}\ge\beta_i \tag{4}$$

Reference [37] proposes that, according to the specific uncertain problem to be solved, the general chance constrained programming can be transferred into the form of goal programming as (5).

$$\min\sum_i\left(u_i^+d_i^+ + u_i^-d_i^-\right) \tag{5a}$$

$$s.t.\ \Pr\left\{f_i\left(x,\xi\right)-k_i\le d_i^+\right\}\ge\beta_i^+ \tag{5b}$$

$$\Pr\left\{k_i-f_i\left(x,\xi\right)\le d_i^-\right\}\ge\beta_i^- \tag{5c}$$

$$d_i^+,d_i^-\ge 0 \tag{5d}$$

The CCGP keeps the chance constraints, which is effective to address uncertainties of renewable energy. With the help of deviation variables in constraints, it provides a way to handle the multi-objective optimization. Meanwhile, by introducing the weighting factors, different importance of distinct constraints could be considered in the model. Enabling more flexibilities, CCGP provides a promising idea to address the uncertain problem with more specific requirements.

B. CCGP Based Dispatch Model

In this subsection, an optimal scheduling model of system with consideration of BESS degradation is formulated on the basis of CCGP. Important assumptions include: i) the probability density functions of wind outputs are known; ii) the probability distributions of different wind farms are independent; iii) only wind uncertainty is taken into consideration.

Three aspects of the day-ahead operation are systematically considered when deciding the system schedules, including the reserve capacity allocation, the total operational cost and the BESS degradation.

1) Reserve capacity allocation

Because of the inherent uncertainties of wind power, the system needs sufficient reserve capacities to guarantee the operational security, which is one of the aspects of optimal dispatching. This reserve constraint is usually formulated in the form of chance constraints [34]. Based on CCGP, the reserve constraints can be formulated as (6a)-(7h).

$$\min\sum_{t\in T}\left(u_1^+d_{1,t}^+ + u_1^-d_{1,t}^-\right) \tag{6a}$$

$$s.t.\ \Pr\left\{\sum_{n\in D}p_{n,t}^d-\sum_{i\in G}p_{i,t}^g-\sum_{j\in E}p_{j,t}^e-r_t^{up}-\sum_{m\in W}\tilde{p}_{m,t}^w\le d_{1,t}^-\right\}\ge\beta^{up} \tag{6b}$$

$$\Pr\left\{\sum_{i\in G}p_{i,t}^g+\sum_{j\in E}p_{j,t}^e-r_t^{dn}+\sum_{m\in W}\tilde{p}_{m,t}^w-\sum_{n\in D}p_{n,t}^d\le d_{1,t}^+\right\}\ge\beta^{dn} \tag{6c}$$

$$d_{1,t}^+\ge 0,\ d_{1,t}^-\ge 0 \tag{6d}$$

$$p_{j,t}^e=p_{j,t}^{dsg}-p_{j,t}^{chg} \tag{7a}$$

$$r_t^{up}=\sum_{i\in G}r_{i,t}^{g,up}+\sum_{j\in E}r_{j,t}^{e,up} \tag{7b}$$

$$r_t^{dn}=\sum_{i\in G}r_{i,t}^{g,dn}+\sum_{j\in E}r_{j,t}^{e,dn} \tag{7c}$$

$$\upsilon_{i,t}p_i^{g\min}+r_{i,t}^{g,dn}\le p_{i,t}^g\le\upsilon_{i,t}p_i^{g\max}-r_{i,t}^{g,up} \tag{7d}$$

$$-p_j^{chg\max}+r_{j,t}^{e,dn}\le p_{j,t}^e\le p_j^{dsg\max}-r_{j,t}^{e,up} \tag{7e}$$

$$p_{j,t}^e-r_{j,t}^{e,dn}\ge\left(c_{j,t-1}-c_j^{\max}\right)/\Delta t \tag{7f}$$

$$p_{j,t}^e+r_{j,t}^{e,up}\le\left(c_{j,t-1}-c_j^{\min}\right)/\Delta t \tag{7g}$$

$$c_{j,t}=c_{j,t-1}+p_{j,t}^{chg}\Delta t\eta_j^c-p_{j,t}^{dsg}\Delta t/\eta_j^d \tag{7h}$$

Equations (6a)-(6d) are the main constraints ensuring sufficient reserve capacities for the power systems with wind power integrated. $d_{1,t}^-$ and $d_{1,t}^+$ present the deviations of upward and downward reserves. $d_{1,t}^-$ may require the unit re-dispatch, and $d_{1,t}^+$ may lead to the wind curtailment. Equation (7a) limits the power output of BESS. Equations (7b)-(7c) formulate the upward/downward reserve constraints. Reference [45] proposed that the reserve capacity of BESS is able to provide ancillary services to address the uncertainties. The reserves from generators and BESS are constrained by (7d) and (7e)-(7g), respectively. Equation (7d) is the power output and the reserve constraint of the generator. The power constraint of BESS reserve is formulated by (7e), and the energy constraints are formulated by (7f)-(7g). Equation (7h) calculates the energy of BESS.

2) Operational cost

The total operational cost is commonly an important index of the day-ahead unit commitment, which should also be considered in the model. According to the CCGP, this objective can be formulated as (8).

$$\min \sum \left(u_2^+ d_2^+ + u_2^- d_2^-\right) \tag{8a}$$

$$s.t.\ C_{op}\left(\upsilon_{i,t}, p_{i,t}^g, p_{j,t}^e\right) + d_2^- - d_2^+ = k_2 \tag{8b}$$

$$\begin{aligned} C_{op}\left(\upsilon_{i,t}, p_{i,t}^g, p_{j,t}^e\right) = & \sum_{t\in T}\sum_{i\in G}\left[su_{i,t}\left(z_{i,t}^{su}\right) + sd_{i,t}\left(z_{i,t}^{sd}\right)\right] \\ & + \sum_{t\in T}\sum_{i\in G}\left(a_i {p_{i,t}^g}^2 + b_i p_{i,t}^g + c_i \upsilon_{i,t}\right) + \sum_{t\in T}\sum_{j\in E}\lambda_{j,t}^e\left(p_{j,t}^{dsg} + p_{j,t}^{chg}\right) \\ & + \sum_{t\in T}\sum_{i\in G}\lambda_{i,t}^{r,g}\left(r_{i,t}^{g,up} + r_{i,t}^{g,dn}\right) + \sum_{t\in T}\sum_{j\in E}\lambda_{j,t}^{r,e}\left(r_{i,t}^{e,up} + r_{i,t}^{e,dn}\right) \end{aligned} \tag{8c}$$

$$d_2^+ \geq 0, d_2^- \geq 0 \tag{8d}$$

Equation (8c) formulates the total operational cost, which consists of startup/shutdown cost, fuel cost, BESS operation cost, reserve costs of generators and BESS. Because SO intends to minimize the operational cost, u_2^- is set to 0 in this paper.

3) Life loss of BESS

Aside from the two aspects mentioned above, BESS degradation is also considered as a primary objective of the scheduling model. According to studies in Section II, the discharge directly affects the life loss of BESS through DoD. Here, with the help of CCGP, we quantify the life loss under different DoDs and consider it when making the scheduling plan. It can be formulated as (9).

$$\min \sum \left(u_3^+ d_3^+ + u_3^- d_3^-\right) \tag{9a}$$

$$s.t. \sum_t NLL_t + d_3^- - d_3^+ = k_3 \tag{9b}$$

$$NLL_t = \left[f_{LL}\left(dod_t\right) - f_{LL}\left(dod_{t-1}\right)\right] / f_{LL}\left(dod^{\max,\min}\right) \tag{9c}$$

$$NLL_t \geq 0 \tag{9d}$$

$$d_3^+ \geq 0, d_3^- \geq 0 \tag{9e}$$

Equations (9c)-(9d) quantify the life loss of the discharge from during [t-1, t], which consider the effect of DoD on BESS life loss. Because the SO intends to minimize the total life losses during the whole dispatch period, u_3^- is set to 0. Thus, the objective function of the whole model can be formulated as (10a). Equations (6b)-(6d), (7), (8b)-(8d) and (9b)-(9e) are also parts of formulations. Other constraints of the day-ahead unit commitment are formulated as (10b)-(10j).

$$\min \sum_t \left(u_1^+ d_{1,t}^+ + u_1^- d_{1,t}^-\right) + u_2^+ d_2^+ + u_3^+ d_3^+ \tag{10a}$$

$$s.t. \sum_{i\in G} p_{i,t}^g + \sum_{j\in E} p_{j,t}^e = \sum_{n\in D} p_{n,t}^d - \sum_{m\in W} p_{m,t}^w \tag{10b}$$

$$p_{i,t}^g - p_{i,t-1}^g \leq \upsilon_{i,t-1} ru_i + z_{i,t}^{su} p_i^{g\min} \tag{10c}$$

$$p_{i,t-1}^g - p_{i,t}^g \leq \upsilon_{i,t} rd_i + z_{i,t}^{sd} p_i^{g\min} \tag{10d}$$

$$z_{i,t}^{su} \geq \upsilon_{i,t} - \upsilon_{i,t-1} \tag{10e}$$

$$z_{i,t}^{sd} \geq \upsilon_{i,t-1} - \upsilon_{i,t} \tag{10f}$$

$$\left(\upsilon_{i,t-1} - \upsilon_{i,t}\right)\left(t_{on,i,t-1} - T_{on,i}\right) \geq 0 \tag{10g}$$

$$\left(\upsilon_{i,t} - \upsilon_{i,t-1}\right)\left(t_{off,i,t-1} - T_{off,i}\right) \geq 0 \tag{10h}$$

$$0 \leq p_{j,t}^{dsg} \leq \upsilon_{j,t}^{dsg} p_j^{dsg\max} \tag{10i}$$

$$0 \leq p_{j,t}^{chg} \leq \upsilon_{j,t}^{chg} p_j^{chg\max} \tag{10j}$$

$$\upsilon_{j,t}^{chg} + \upsilon_{j,t}^{dsg} \leq 1 \tag{10k}$$

$$c_j^{\min} \leq c_{j,t} \leq c_j^{\max} \tag{10l}$$

Equation (10b) is the power balance constraint. Equations (10c)-(10d) are the ramping constraints of the thermal unit, which also guarantee that ramping constraints are met when the unit startup or shutdown. Equations (10e)-(10f) are logic constraints of thermal unit states. Equations (10g)-(10h) limit the minimal on/off duration of the thermal unit. Equations (10i)-(10j) are the power output constraint of BESS. Equation (10k) limits the maximal/minimal capacity of BESS.

C. *Remarks*

In this model, the effect of DoD on BESS degradation is considered as one objective of the multi-objective optimization problem, rather than be transferred as part of costs [46]. If the life loss is considered as part of the investment cost in daily dispatch model, it is relatively high comparing with the operational cost of thermal generators. Thus, the BESS would not be discharged, indicating the inefficient management of the BESS. In addition, the life loss is sensitive to the BESS discharge, which means that the discharge may multiply the effect on the total cycle life of BESS. Apart from this, the setting of the corresponding weighting factor reflects how much emphasis is given to the life loss of BESS. As the BESS technology matures, this factor would become smaller. And it also can vary according the SO's attitude towards the optimal management of BESS.

IV. MODEL TRANSFORMATION AND SOLUTION

A. *Deterministic Equivalent of Chance Constraints*

In order to improve the solving efficiency, we intend to transfer the chance constraints to their deterministic equivalent. Reference [41] proposes that the chance constraint can transfer to its deterministic form when stochastic variables in constraint can be separated from decision variables. And the stochastic variable with explicit cumulative distribution function can be directly calculated by the inverse function. The theory above makes it feasible to reformate the chance constrains (6b)-(6c) as (11a)-(11b), where $\varphi^w(\ )$ is the inverse cumulative distribution function of wind power output.

$$d_{1,t}^- = \sum_{n\in D} p_{n,t}^d - \sum_{i\in G} p_{i,t}^g - \sum_{j\in E} p_{j,t}^e - r_t^{up} - \varphi^w\left(1 - \beta_t^{up}\right) \tag{11a}$$

$$d_{1,t}^+ = \sum_{i\in G} p_{i,t}^g + \sum_{j\in E} p_{i,t}^e - \sum_{n\in D} p_{n,t}^d - r_t^{dn} - \varphi^w\left(\beta^{dn}\right) \tag{11b}$$

B. *Linearization of the life loss*

The life loss of BESS is the function of DoD, which is monotonically increasing. Thus, the life loss function can be linearized through the big M method [47]. The DoD range can be divided into Q pieces. Then, equation (3c) can be reformulated as (12). And (12a) can be also transferred to (12c).

$$NLL_{j,t} \geq K_{q,j}\left(dod_{j,t} - dod_{j,t-1}\right) - M\left(1 - R_{q,j,t}\right) \quad dod_{j,t} \geq dod_{j,t-1}, \quad q = 1,2,\cdots,Q \tag{12a}$$

$$R_{q,j,t} = \begin{cases} 1, \ when \dfrac{dod_{j,t} - dod_{j,t-1}}{2} \in \left(\dfrac{q-1}{Q}, \dfrac{q}{Q}\right] \\ 0, \ others \end{cases} \tag{12b}$$

$$NLL_{j,t} \geq K_{q,j} p_{j,t}^{dsg} \Delta t / c_j^{\max} - M\left(1 - R_{q,j,t}\right), q = 1,2,\cdots,Q \tag{12c}$$

Furthermore, equation (8c) could be reformulated to linear functions through the same way, as shown above.

C. Solution

After the transformation above, the reformulated model is a convex MILP. And it could be solved by CPLEX 12.6.

V. Case Study

A. Case Description

The simulation is carried out based on a modified IEEE-39 Bus Test System. The technical and commercial parameters of thermal units could be found in [48]. The load profile and wind power output of the following day are obtained by [49] and shown in Fig.2. The probability density function of wind forecasting error is defined by the normal distribution in (13a), with the standard deviation $\sigma_{m,t}^{w}$ calculated in (13b) [50]. The confidence level for all chance constrains is set to 0.99. k_2 and k_3 are both set to 0.

$$\tilde{p}_{m,t}^{w} \sim N\left(\bar{p}_{m,t}^{w}, \sigma_{m,t}^{w}\right) \tag{13a}$$

$$\sigma_{m,t}^{w} = 0.2\bar{p}_{m,t}^{w} + 0.02 p_m^{w\max} \tag{13b}$$

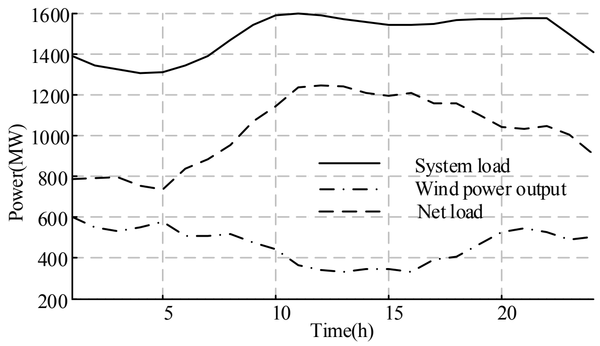


Fig.2 Load profile and wind power output

The charging and discharging efficiency of BESS are set to 0.9. The maximum charging and discharging rate of BESS are set to 150 MW, and the capacity of BESS is 600MWh. Maximum and minimum energy stored in BESS are set to 540MWh and 60 MWh, respectively. The relationship between the life loss and DoD is obtained from Fig. 1(b). The reserve price of BESS is set to 5 \$/MWh. The weight factor u_1^-, u_1^+, u_2^+ and u_3^+ are set to 20, 100, 1 and 3000 respectively.

To verify the effectiveness of the proposed method, the obtained simulation results are compared with a case without considering the BESS degradation and a case with linear BESS degradation. For simplicity, the case without considering the BESS degradation is denoted by “WBDeg”, the linear BESS degradation case is denoted by “LBDeg”, and the proposed method with nonlinear degradation is denoted by “NBDeg”.

The WBDeg case is based on the classical CCP method, in which the objective function is to minimize the total operation cost as shown in (8c). The reserve constraints are based on the traditional CCP, and confidence levels for all chance constrains are the same as in other two cases. It also subjects to other system constraints (6b)-(6d) and (7). The difference between the LBDeg case and NBDeg case lies in the degradation characteristics of BESS. It is nonlinear in NBDeg (as shown in Fig.1(b)), while it is linear in LBDeg. In LBDeg, the relationship between the life loss of BESS and DoD is assumed linear, with the average slope in Fig.1(b).

The reformulated models in three cases are all convex MILP, and solved by CPLEX 12.6. The simulation is implemented on a computer with i4770 CPU and 16GB RAM.

B. Effect of Considering BESS Degradation

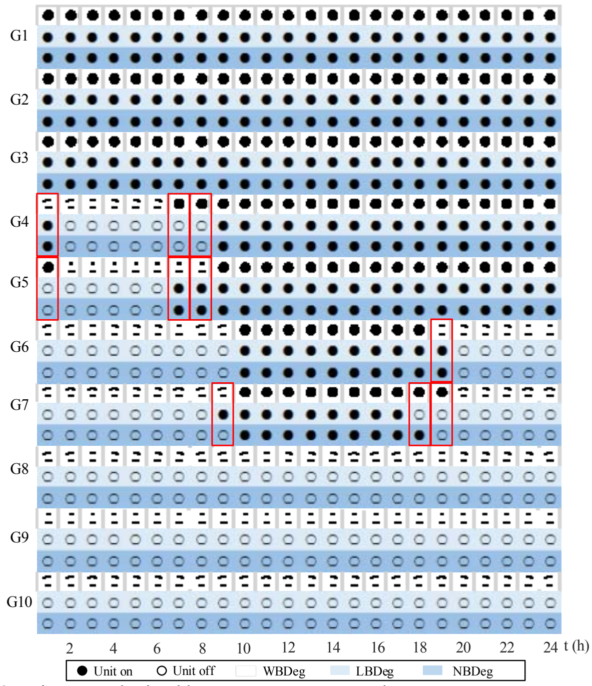


Fig.3 Unit status obtained by WBDeg, LBDeg and NBDeg cases

The unit states of thermal units obtained by the three methods are presented in Fig.3. The output of each generation and BESS are given in Fig.4. As shown in Fig.3, unit 4~unit 7 have different operational states. The difference among the unit schedules result in distinct generation outputs in Fig.4. This is owing to the difference of BESS operations under different methods, when the power balance constraint (10b) is satisfied, as shown in Fig.4. Considering the net load profile in Fig.2, the BESS are charged during light load period as shown in Fig.4, i.e., 0:00~5:00. Meanwhile, the BESS are discharged during heavy load periods. However, compared with WBDeg case, the BESS is discharged much less in LBDeg and NBDeg cases, observed from Fig.4. It indicates that when considering the life loss of BESS, the SO can obtain more practical operation solutions to optimally utilize the BESS.

The DoD of BESS in the simulation day is given in Fig.5. Considering the output profiles of BESSs during 21:00-24:00, DoD of BESS in NBDeg is smaller than the DoD in LBDeg and WBDeg, depicted by Fig.5. It indicates that when applying the nonlinear life loss model, the discharge of BESS is much smaller in NBDeg. As shown in (9), smaller DoD can reduce the life loss of BESS, vice versa. This verifies that the proposed method can prevent over-discharging of BESS, reducing the life loss of BESS.

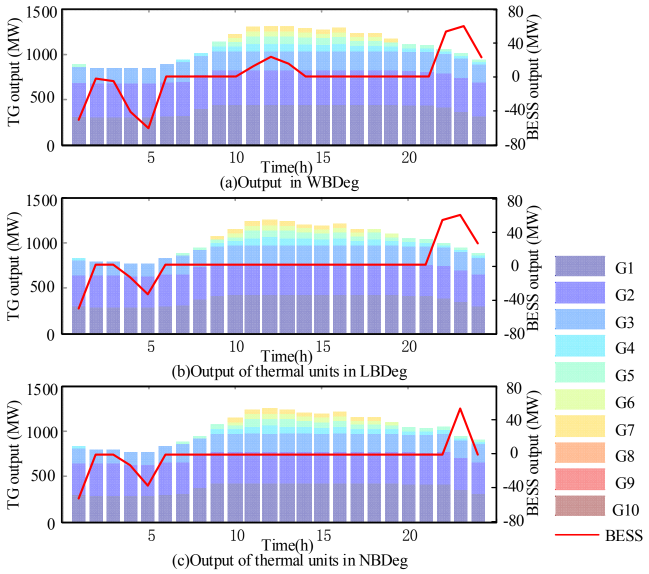


Fig.4 Outputs in WBDeg, LBDeg and NBDeg cases

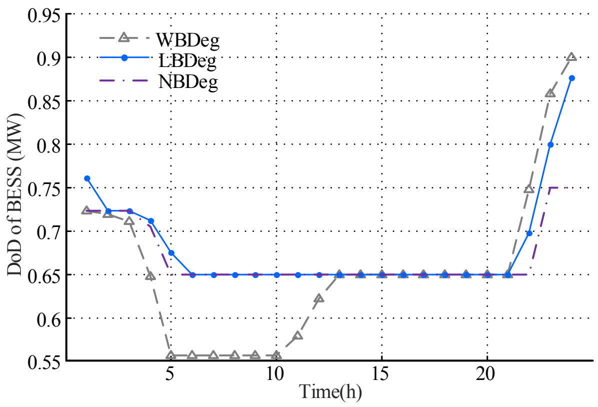


Fig.5 DoD of BESS in WBDeg, LBDeg and NBDeg cases

TABLE I
OPERATION COST AND LIFE LOSS OF BESS

Case	Operation cost	Life loss of BESS[1]
WBDeg	379,429.57 $	0.9325
LBDeg	379,462.22 $	0.7268
NBDeg	380,723.97 $	0.2317

Note:1. Life loss of BESS is calculated by (1)-(3).

The operation cost and BESS life loss of all cases are given in Table I. Compared with WBDeg case, the operation cost of LBDeg increases to 379,462.22 $, which is due to that the BESS is not discharged at 12:00, observed from Fig.4. The operation cost of NBDeg case increases to 380,723.97 $ by 0.34%, as the BESS discharges least in NBDeg, as shown in Fig.4. The life loss of BESS is significantly reduced from 0.9325 to 0.2317 and 0.7268, by accounting the life loss of BESS through linear model and nonlinear model, respectively.

The results shown in Table I indicate that, by scarifying a little operation efficiency, i.e., a slight increase of operation cost, the life loss of BESS can be reduced remarkably. Therefore, the proposed CCGP based model can balance the total operation cost and life loss of BESS simultaneously, under different life loss models of BESS.

C. Sensitive analysis

As shown in [51], the cost of BESS is decreasing tremendously. To study the impact of BESS cost on the system operation, simulations under various weight factors u_3^+s are carried out. The operation cost and life loss of BESS are shown in Fig.6.

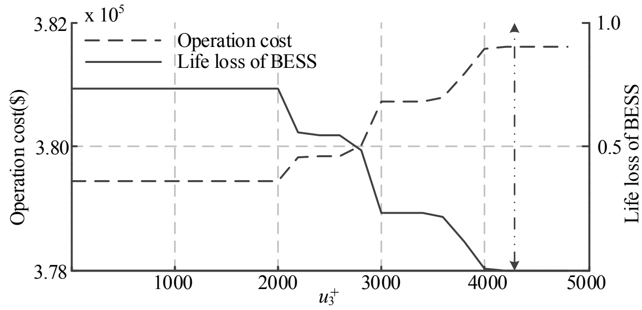


Fig.6 Relationship between operation cost/life loss of BESS and u_3^+

As shown in Fig.6, the operation cost increases while the life loss of BESS decreases with the increment of u_3^+. However, when u_3^+ is bigger than 4200, the life loss of BESS and operation cost would not change. In addition, the life loss of BESS is 0, which means BESS would not be discharged when u_3^+ reaches to 4200 according to (12c). The simulation results above further demonstrates the effectiveness of the proposed method in accounting for BESS's life loss. Furthermore, these results also reveal the fact that u_3^+ plays an important role in balancing the operation of BESS and other power sources, i.e., thermal units in this paper.

As shown in (6b)-(6c), the confidence level β defines the risk level, which the day-ahead operation must satisfy. The operation cost and life loss of BESS under different confidence level β are shown in Fig.7, where u_3^+ is fixed to 3000. As shown in Fig.7, the operation cost increases with the increment of confidence level β, while the life loss of BESS is not strongly affected by the confidence level β.

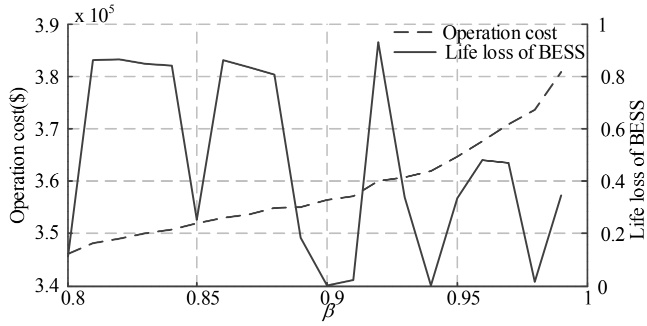


Fig.7 Relationship between operation cost/life loss of BESS and β

D. Long-term simulation result

To further verify the effectiveness of the proposed method, a long-term simulation during April 1st, 2015 - May 30th, 2015, i.e. 60 days, has been carried out. The SoC of BESS at each time period and operation cost (8c) of each day are shown in Fig.8 and Fig.9, respectively.

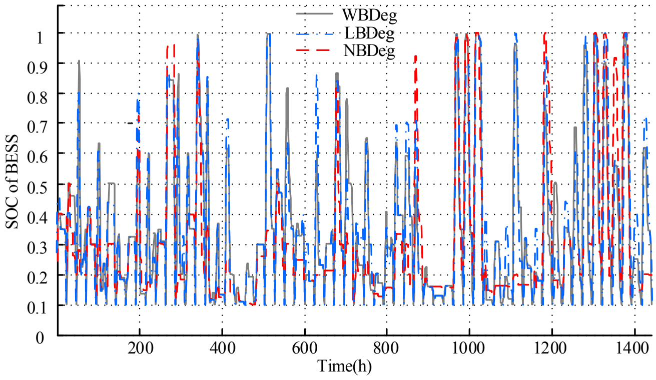


Fig.8 SoC of BESS along the simulation period

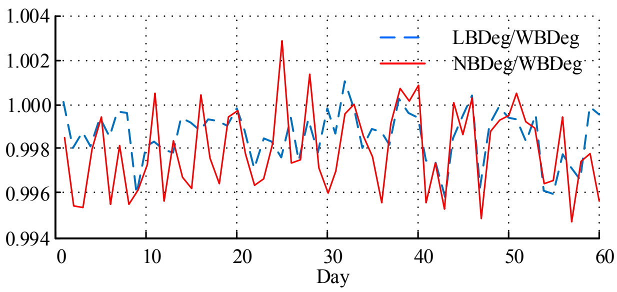


Fig.9 Operation costs along the simulation period.

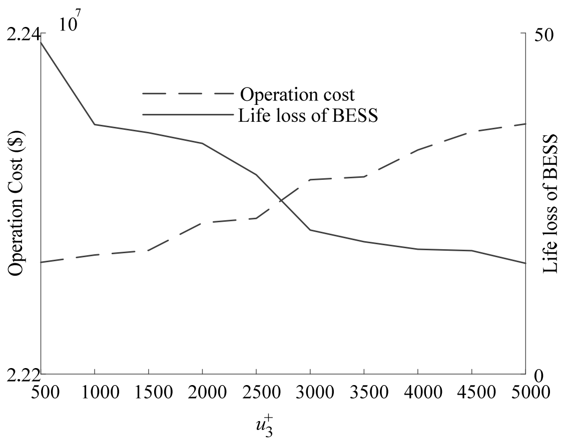


Fig.10 Relationship between operation cost/life loss of BESS and u_3^+ in the long-term simulation

As shown in Fig.8, when the SoC is relatively low, the SoC curve of NBDeg is higher than that of LBDeg and WBDeg in most of periods. It indicates that the proposed method can prevent over-discharging of BESS, compared with the LBDeg and WBDeg methods. An interesting observation of Fig.9 is that, there are only slight differences between operation costs of WBDeg, LBDeg and NBDeg in each simulation day. The total operation cost of NBDeg along the simulation period is 22,223,646.93$, which is 0.029% higher than the operation cost of LBDeg (22,217,110.22$) and 0.088% higher than WBDeg (22,204,117.78$). The simulation results above have shown that the proposed method can capture the operation characteristics of BESS while guaranteeing the efficiency of the system operation.

In addition, to show the impacts of weight factors u_3^+s on the long-term performance of the proposed method, a sensitive analysis of life loss of BESS and operation cost with respect u_3^+ is given in Fig.10. As shown in Fig.10, the operation cost increases while the life loss of BESS decreases with the increment of u_3^+ in the long run. Considering (10a), it can be interpreted that SO needs to increase the operation cost to avoid the life loss of BESS, when u_3^+ is pretty high.

VI. Conclusion

A novel CCGP method is proposed in this paper for the system operator to optimally decide the day-ahead unit commitment while considering the degradation cost characteristics of BESS. In this method, the unit commitment and BESS are simultaneously scheduled on the basis of CCGP based method. The operation cost and degradation of BESS are comprehensively considered by introducing different weight factors for each objective. This method is modeled as a chance constrained mix-integer nonlinear optimization problem, which is non-convex. The problem is reformulated to a mix-integer convex quadratic constrained problem based on deterministic equivalent of chance constraints and linearization technique, which could be solved efficiently by commercial software packages.

To verify the effectiveness of the proposed method, the simulations are carried out on a modified IEEE-39 bus test system with BESS integrated. The simulation results show that, i) the unit commitment plan is affected by the degradation cost of BESS, ii) compared with traditional CCP based method, the proposed method could simultaneously consider the operation cost and BESS degradation, and iii) both the weight factor and confidential level could affect the operation cost, while the life loss of BESS is strongly related to the weight factor of BESS degradation.

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