DAY-AHEAD SCHEDULING FOR AN ELECTRIC VEHICLE PV-BASED BATTERY SWAPPING STATION CONSIDERING THE DUAL UNCERTAINTIES

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ABSTRACT

So far, the day-ahead scheduling research of photovoltaic (PV)-based battery swapping stations (BSSs) has not fully considered the uncertainties of swapping demand and PV output. To address this issue, a day-ahead economic scheduling method based on chance-constrained programming and probabilistic sequence operation is proposed in this paper. First of all, a BSS day-ahead scheduling model with chance constraints as swapping demand satisfaction and the confidence level of the minimum cost is established. The confidence level of chance constraints is set by BSS operators. Then, probabilistic sequences of stochastic variables are constructed, and the quantitative index to measure the day-ahead scheduling risk of BSS is proposed based on sequence operation. Thereafter, the feasible solution space is determined based on the battery controllable load margin, and then the fast optimization method for the BSS day-ahead scheduling model is developed by combining the feasible solution space and genetic algorithm (GA). Finally, the validity and applicability of the proposed method is verified in the case study.

Keywords: PV-based battery swapping station, dayahead scheduling, chance-constrained programming, uncertainties, probabilistic sequence

NONMENCLATURE

	A sign that a negative number returns	
	to zero.	
Θ	Subtraction-type convolution operation	
\oplus	Addition-type convolution operation	
\odot	Sequence multiplication operation	
р	Unit price of purchase electricity from	

$P_{b} P_{PV}$ $P_{r} \{\cdot\}$ N_{need} N_{s} \overline{f}	the utility grid Batteries charging load and PV power The probability that the event is true The number of swapping demand The number of available batteries The minimum value taken by the electricity cost function when the confidence level is not lower than β	
$f\left(P_{b},P_{PV}\right)$	Electricity cost function	
$egin{aligned} P_{\scriptscriptstyle PVr} \text{ , } P_{\scriptscriptstyle PVf} \ e(t) \ \sigma_{\scriptscriptstyle PV,t} \end{aligned}$	Actual/predicted value of PV output Prediction error of PV output at time t The standard deviation of $e(t)$	
$P_{_{PV,t}}\left(i_{_{PVt}} ight)$	Probabilistic sequence of PV output	
$f_{PV,t}(x)$	Probability distribution function of P_{PV}	
ΔP , Δp	The discretization step size of PV output/ the TOU price	
$N_{PV,t}$	The length of the sequence $P_{_{PV,t}}ig(i_{_{PVt}}ig)$	
$P_{b,t}\left(i_{bt} ight)$	Probabilistic sequence of P_b	
$C_{t}(i_{Ct})$	Probabilistic sequence of electricity cost in time t	
$p_t(i_{pt})$	Probabilistic sequence of p at time t	
$F(i_F)$	Probabilistic sequence of daily electricity cost	
$D_{NSt}\left(i_{Dt} ight)$	Probabilistic sequence of the unmet swapping demand at time t	
$N_{need,t}(i_{Nt})$	Probabilistic sequence of $N_{need}(t)$	
$N_{_{St}}\left(i_{_{st}} ight)$,	Probabilistic sequence of	
$N'_{St}\left(i'_{st}\right)$	planed/updated N_s at time t	
ΔN_t ' (i_t)	Probabilistic sequence of the number of remaining available batteries	
f_{under}	The undervalued part of electricity cost	
$\lambda_{_{dns}}$, $\lambda_{_{under}}$	The unit penalty for not meeting the swapping demand / the underestimation of electricity cost	

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1. INTRODUCTION

Recently, with the increase in the number of electric vehicles (EVs), the charging service has been widely concerned. The battery swapping mode not only enable the rapid battery energy replenishment, but also enables orderly charge management of batteries, so it could be considered as the most economical and efficient alternative mode. The addition of PV output can more effectively reduce energy cost [1-3].

The day-ahead economic scheduling of PV-based BSSs needs to take into account uncertain factors during the actual operation process. At present, scholars have carried out some initial relevant research work, including short-term forecasting, Monte Carlo simulation and multi-scene technology to deal with the uncertainties of swapping demand or PV output [3]-[5]. Most studies have used the typical cases of uncertain factors to represent uncertainties. However, one major drawback of these methods is that the timing combination of the actual values of uncertain factors inevitably deviates from the above typical cases, thus affecting the economy and applicability of day-ahead scheduling results in actual operation.

In order to solve the above problem, the probabilistic sequence is used to describe the dual uncertainties of swapping demand and PV output in this paper, which can cover the timing combination of any possible value of uncertain factors in actual operation. The obtained scheduling scheme has stronger applicability to the changes of uncertain factors.

Considering different risk appetite of operators, the chance-constrained programming with flexible choice of confidence level is adopted to establish the economic operation model of the BSS in this paper, and then the relationship between the economy and risk is measured.

For the problem of solving the BSS scheduling model, the algorithm used to solve this problem is compared in [6], and the results indicate that the performance of the GA and differential evolution algorithm is better than particle swarm optimization. In [7], GA is used to solve the economic operation model of the BSS, and removed the new individuals which did not meet the conditions generated by the genetic operation. But this operation is detrimental to the diversity of the population. Due to the complexity and timing correlation of the BSS scheduling model, how to ensure the feasibility of the solution and remain the efficiency of the algorithm are the key issues needed to be paid attention to in the research. In [8], for the dynamic classification of EVs, the energy limitation calculation model is proposed to determine the upper and lower limits of the controllable energy. The results were used to design the charging power allocation algorithm. The controllable load margin of the batteries in the BSS proposed in [9] has great guiding significance for the BSS operator to formulate the corresponding charging plan according to the grid operation requirements. By using the controllable load margin of batteries in the BSS proposed in [9] to determine the feasible solution space, a fast optimization method for the BSS day-ahead scheduling model is proposed.

2. DAY-AHEAD SCHEDULING OF THE BSS BASED ON CHANCE-CONSTRAINED PROGRAMMING

2.1 Objective function

The objective function is to minimize the cost of electricity purchased from the utility grid, as follows:

$$\min F = \sum_{t=1}^{24} \left\lfloor P_b(t) - P_{PV}(t) \right\rfloor \cdot p(t)$$
(1)

2.2 Constraints

The probability of the actual swapping demand satisfaction should not be lower than the given confidence level α .

$$P_r\left\{N_{need}\left(t\right) \le N_s\left(t\right)\right\} \ge \alpha \tag{2}$$

The probability that the electricity cost of the dayahead scheduling plan for the actual operation does not exceed the objective value should not be lower than the given confidence level β .

$$P_r\left\{f\left(P_b, P_{PV}\right) \le \overline{f}\right\} \ge \beta \tag{3}$$

In this paper, batteries charging load should not exceed the upper and lower limits proposed in [9].

$$P_{\min}\left(t\right) \le P_{b}\left(t\right) \le P_{\max}\left(t\right) \tag{4}$$

3. CHANCE CONSTRAINTS PROCESSING METHOD BASED ON PROBABILISTIC SEQUENCES

3.1 Probabilistic serialization of stochastic variables

3.1.1 Probabilistic sequence and its operation theory

In [10], the probabilistic sequence is defined as: a discrete sequence a(i) with known length N_a , if it satisfies: $0 \le a(i) \le 1$ and $\sum_{i=0}^{N_a} a(i) = 1$, the sequence is called a probabilistic sequence.

Two discrete sequences $a(i_a)$ with known length N_a and $b(i_b)$ with known length N_b are used as the

original sequences, and the following operations are defined.

(1) Addition-type convolution operation

$$x(i) = \sum_{i_a+i_b=i} a(i_a)b(i_b)$$
 $i = 0, 1, \dots, N_x$ (5)

Where $N_x = N_a + N_b$. The operation defined by Eq (5) is the addition-type convolution operation. The sequence x(i) of length N_x is the addition-type convolution sequence of $a(i_a)$ and $b(i_b)$, which can be denoted as

$$x(i) = a(i_a) \oplus b(i_b) \tag{6}$$

(2) Subtraction-type convolution operation

$$y(i) = \begin{cases} \sum_{i_{a}-i_{b}=i} a(i_{a})b(i_{b}) & 1 \le i \le N_{y} \\ \sum_{i_{a}\le i_{b}} a(i_{a})b(i_{b}) & i = 0 \end{cases}$$
(7)

Where $N_y = N_a$. The operation defined by Eq (7) is the subtraction-type convolution operation. The sequence y(i) of length N_y is the subtraction-type convolution sequence of $a(i_a)$ and $b(i_b)$, which can be denoted as

$$x(i) = a(i_a)\Theta b(i_b)$$
(8)

(3) Sequence multiplication operation

$$s(i) = \begin{cases} \sum_{i=i_{a}i_{b}} a(i_{a})b(i_{b}) & i = i_{a}i_{b} \\ 0 & i \neq i_{a}i_{b} \end{cases} \qquad i = 0, 1, \dots N_{s}$$
(9)

Where $N_s = N_a N_b$. The operation defined by Eq (9) is the sequence multiplication operation. The sequence s(i) of length N_s is the sequence multiplication operation result of $a(i_a)$ and $b(i_b)$, which can be denoted as

$$s(i) = a(i_a) \odot b(i_b) \tag{10}$$

3.1.2 Probability serialization of PV generation

The PV generation value can be expressed by the sum of the short-term predicted value and predicted error as is shown below,

$$P_{PVr}(t) = P_{PVf}(t) + e(t)$$
(11)

Where e(t) can be represented by the normal distribution $N(0, \sigma_{PV,t})$, and the standard deviation is 10% of the predicted value. The predicted value is used as the mean value to construct the probability density function (PDF) of PV output.

PV output timing multi-state probabilistic sequence represents the probability of different PV output states in each period, which can be calculated as Eq (12).

$$P_{PV,t}(i_{PVt}) = \begin{cases} \int_{0}^{\frac{\Delta P}{2}} f_{PV,t}(x) dx & i_{PVt} = 0\\ \int_{i_{PVt}\Delta P - \frac{\Delta P}{2}}^{i_{PVt}\Delta P + \frac{\Delta P}{2}} f_{PV,t}(x) dx & 0 < i_{PVt} < N_{PV,t} \end{cases}$$
(12)
$$\int_{i_{PVt}\Delta P - \frac{\Delta P}{2}}^{i_{PV}\Delta P + \frac{\Delta P}{2}} f_{PV,t}(x) dx & i_{PVt} = N_{PV,t} \end{cases}$$

3.1.3 Probability serialization of swapping demand

The Monte Carlo simulation result of swapping demand in [9] is used as the predicted value. The timing multi-state probabilistic sequence of swapping demand is calculated in the same way as $P_{PV,t}(i_{PVt})$.

3.2 Sequence operation results of the objective function

According to [5], the probabilistic sequence of the all-day electricity cost in the objective function is obtained by sequentially using the subtraction-type convolution, sequence multiplication, and addition-type convolution operations as is shown below

$$C_{t}\left(i_{C_{t}}\right) = \left(P_{b,t}\left(i_{bt}\right)\Theta P_{PV,t}\left(i_{PVt}\right)\right) \odot p_{t}\left(i_{pt}\right)$$
(13)

$$F(i_F) = C_t(i_{C1}) \oplus C_t(i_{C2}) \oplus \cdots \oplus C_t(i_{C24})$$
(14)

3.3 Deterministic transformation of chance constraints

The cumulative probability corresponding to different values of stochastic variables can be calculated by probabilistic sequence of stochastic variables. According to the cumulative probability, the value satisfying the chance constraint can be obtained, so that the chance constraint can be transformed into a deterministic constraint. The specific methods are described below.

In Section 3.1.3, the possible value of swapping demand in the t-th period is divided into $N_{\rm Nneed,t}$ +1 states, and the probability corresponding to each state is

$$P(N_{need,t} = i_{Nt}) = N_{need,t}(i_{Nt}), i_{Nt} = 0, 1, \dots, N_{Nneed,t}$$
(15)

Then, the cumulative probability corresponding to each state of swapping demand in the t-th period is

$$F_{N_{need,t}}(x) = P(N_{need,t} \le x) = \sum_{i_{N_{t}}=0}^{x} N_{need,t}(i_{N_{t}})$$
(16)

In order to satisfy the chance constraint in Eq (2), it is assumed that the minimum number of available batteries in the t-th period is N_{St} . Then N_{St} should satisfy:

$$\begin{cases} F_{N_{need,i}}(N_{St}-1) < \alpha \\ F_{N_{need,i}}(N_{St}) \ge \alpha \end{cases}$$
(17)

 N_{st} can be obtained from Eq (17). In Eq (2), $N_{s}(t) = N_{st}$.

Similarly, the deterministic transformation of chance constraint in Eq (3) can be performed, and \overline{f} can be obtained.

4. RISK ANALYSIS FOR DAY-AHEAD SCHEDULING OF THE PV-BASED BSS

4.1 Risk of unmet swapping demand

Due to the uncertainty of swapping demand, the actual value of swapping demand may be more or less than the number of batteries available in the BSS. There is a certain probability that the chance constraint in Eq (2) is not satisfied. Therefore, considering the economy and user satisfaction, the following rules for the BSS actual operation are formulated: 1) The number of batteries available in the BSS is updated every time period. 2) If the current swapping demand is lower than the number of available batteries, the number of available batteries in the next period increases the number of currently remaining available batteries. 3) If the current swapping demand is higher than the number of available batteries, the extra swapping demand will not be met.

The probabilistic sequence of the unmet swapping demand in the t-th period can be calculated by sequence operation as is shown below

$$D_{NSt}(i_{Dt}) = N_{need,t}(i_{Nt})\Theta N'_{St}(i'_{st})$$
(18)

$$N'_{St}(i'_{st}) = N_{St}(i_{st}) \oplus \Delta N'_{t-1}(i_{t-1})$$
(19)

$$\Delta N_t'(i_t) = N'_{St}(i'_{st}) \Theta N_{need,t}(i_{Nt})$$
(20)

The mathematical expectation of unmet swapping demand can be calculated as Eq (12).

$$E(D_{NS}(t)) = \sum_{i_{Dt}=0}^{N_{Dt}} i_{Dt} D_{NSt}(i_{Dt})$$
(21)

4.2 Risk of underestimation of costs

Due to the influence of PV output on the forecast error, the electricity cost may be underestimated, and the mathematical expectation of the undervalued part can be expressed by the following equation.

$$E(f_{under}) = \sum_{i_F}^{N_F} f_{under}(i_F) F(i_F)$$
(22)

Where,

$$f_{under}\left(i_{F}\right) = \begin{cases} 0 & i_{F}\Delta P\Delta p \le \min \overline{f} \\ i_{F}\Delta P\Delta p - \min \overline{f} & i_{F}\Delta P\Delta p > \min \overline{f} \end{cases}$$
(23)

4.3 The penalty cost corresponding to the risk of dayahead scheduling

The penalty cost corresponding to the risk of dayahead scheduling can be calculated as Eq (24).

$$C_{risk} = \sum_{t=1}^{24} E(D_{NS}(t))\lambda_{dns} + E(f_{under})\lambda_{under}$$
(24)

5. FAST OPTIMAIZATION METHOD BASED ON DETERMINING FEASIBLE SOLUTION SPACE

In this paper, the batteries charging load of each period is the decision variable in the day-ahead scheduling model. By using the controllable load margin of batteries in the BSS proposed in [9] to determine the feasible solution space, the operation of eliminating the infeasible solution in GA is avoided, and the optimization efficiency of GA can be improved. In order to represent the position of batteries charging load in the feasible solution space, 24 stochastic numbers $x(t) \in [0,1]$ are set as decision variables in GA.

$$P_{b}(t) = P_{\min}(t) + x(t)(P_{\max}(t) - P_{\min}(t))$$
(25)

The specific process of using GA to solve the



Fig 1 GA solution flow chart

economic operation model of the BSS is shown in Fig. 1.

6. CASE STUDY

It is assumed that there are 1,000 EVs in the service area of the BSS. The number of batteries in the BSS is 600. The number of chargers is 350. The average charging power of a battery is 5kW with 50kWh battery capacity. The minimum and maximum charge capacities of the battery are 20%, and 90% respectively. The TOU price for electricity purchased from the utility grid refers to the data in [7].

The PV installation capacity of the BSS is 240 kW. The typical summer PV output data is selected as the PV output prediction parameter. The discretization step size is 2.5 kW. Time-series multi-state probabilistic sequences of PV output and swapping demand are shown in Fig. 2, which represents the probability of different values in each period.

Case 1: multi-scene technology is used to deal with uncertain factors in the BSS day-ahead scheduling. The feasible solution space determined according to [9] is adopted to solve the model.

Case 2: probabilistic sequence is used to deal with uncertain factors in the BSS day-ahead scheduling. The feasible solution space determined according to [9] is adopted to solve the model.

Case 3: probabilistic sequence is used to deal with uncertain factors in the BSS day-ahead scheduling. The feasible solution space determined according to [9] is not adopted to solve the model.

6.1 Comparison of processing methods for uncertain factors

Charging plans for the above three cases are separately formulated. When $\alpha = 0.8$ and $\beta = 0.9$, the values of the costs of Case 1 and Case 2 are shown in Table 1. There is little difference in electricity cost between the two cases, which proves the effectiveness of the proposed method in this paper. In addition, the penalty cost of Case 2 is much lower than that of Case 1. This is because the scenario reduction of multi-scene technology sacrifices the comprehensiveness of considering the uncertainty, which makes it more likely to underestimate the electricity cost or fail to meet the swapping demand compared with the method proposed in this paper.

Table 1. Costs of Case1 and Case 2						
Cases	Casos	Electricity cost	The penalty cost	Total cost		
	Cases	(yuan)	(yuan)	(yuan)		
	Case 1	6296.2	325.1	6621.3		
	Case 2	6276.1	58.6	6334.7		



Fig 2 Time-series multi-state probabilistic sequences



Fig 3 Probabilistic sequence of electricity cost per hour

6.2 Analysis of electricity cost probabilistic sequence

Fig. 3. presents the probability of different electricity costs in each period in Case 2. It can be seen from Fig. 3 that the uncertainty of PV output is large in the 11am-3pm with a large average PV output. The wider the range of possible charging costs, the greater the uncertainty is. At 2pm, due to the lower charging load of the BSS, the PV output can fully bear the battery charging load in a certain probability, and the BSS does not need to purchase electricity from the grid. As a result, the charging cost is zero during this period. On the contrary, during the time when the average PV output is small, the cost floatation is smaller when the range of possible charging becomes narrow.

6.3 Comparison of optimization methods

In order to illustrate the superiority of the proposed fast determining the feasible solution space based optimization method, the undefined feasible solution space method and the proposed method are used to calculate the above case, respectively. The GA parameters of the two methods are consistent, and the corresponding iterative curve is shown in Fig. 4. It can be seen from Fig. 4 that the proposed optimal value based on the determination of the feasible solution space has stabilized at 400 generations, and the optimal average value is approached. The convergence speed of



Fig 4 Evolutionary curves of Case 2 and Case 3

the unconstrained feasible solution space is different from that of the proposed method, and the method falls into local optimum many times. Compared with the method that does not define the feasible solution space, the proposed method has improved the optimization ability, which indicates that the proposed method has advantages. From this research, the comparative method still does not converge at 500 generations, and there is still a certain gap in the optimal value between the two methods. This is because that the introduction of the feasible solution space makes the individuals generated by the genetic operation feasible, and avoids the damage to the population diversity due to the elimination of the infeasible individuals. In the case of the same population size, the proposed method improves the global diversity of the algorithm and achieves the goal of searching the optimization solution efficiently.

7. CONCLUSION

Due to the influence from the uncertainty of swapping demand and PV output on the day-ahead dispatching of the BSS, the probabilistic sequence is adopted to describe the stochastic variables. The chance-constrained programming is introduced into the economic operation model of the BSS. Compared with the multi-scene technology method, the advantages of using the probabilistic sequence are analyzed. A fast optimization method for the BSS scheduling model has been developed. The simulation results show that the proposed method has a higher tolerance to uncertainties and has the ability to improve the solving efficiency. Results illustrate that the model can provides a more reasonable charging strategy for the BSS operators with different risk appetite.

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