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Day-Ahead Scheduling for an Electric Vehicle PV-Based Battery Swapping Station Considering the Dual Uncertainties

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ABSTRACT A day-ahead economic scheduling method based on chance-constrained programming and probabilistic sequence operation is proposed in this paper for an electric vehicle (EV) battery swapping station (BSS), considering the dual uncertainties of swapping demand and photovoltaic (PV) generation. First of all, a BSS day-ahead scheduling model that can deal with the uncertainties is established by using the chance-constrained programming. The optimization objective is to minimize the cost of electricity purchased from the utility grid with the chance constraints of swapping demand satisfaction and the confidence level of the minimum cost. Then, the deterministic transformation of chance constraints is implemented based on probabilistic sequences of stochastic variables. Thereafter, the feasible solution space of the proposed model 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). In order to evaluate the solution quality, a risk assessment method based on the probabilistic sequence for day-ahead scheduling solutions is proposed. Finally, the efficiency and applicability of the proposed method is verified through the comparative analysis on a PV-based BSS system. Results illustrate that the model can provides a more reasonable charging strategy for the BSS operators with different risk appetite.

INDEX TERMS PV-based battery swapping station, day-ahead scheduling, chance-constrained programming, uncertainties, probabilistic sequence.

NOMENCLATURE

Θ	Subtraction-type convolution operation
$\oplus$	Addition-type convolution operation
$\circledcirc$	Sequence multiplication operation
p	Unit price of purchase electricity from the utility grid
P_b, P_{PV}	Batteries charging load and PV power
$P_r\{\cdot\}$	The probability that the event is true
N_{need}	The number of swapping demand
N_s	The number of available batteries
$\bar{f}$	The minimum value taken by the electricity cost function when the confidence level is not lower than β
$f(P_b, P_{PV})$	Electricity cost function
P_{PVr},P_{PVf}	Actual/predicted value of PV output
$e(t)$	Prediction error of PV output at time t
$\sigma_{PV,t}$	The standard deviation of $e(t)$
$P_{PV,t}(i_{PVt})$	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 $P_{PV,t}(i_{PVt})$
$P_{b,t}(i_{bt})$	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
$D_{NSt}(i_{Dt})$	Probabilistic sequence of the unmet swapping demand at time t

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$N_{need,t}\left(i_{Nt}\right)$	Probabilistic sequence of $N_{need}\left(t\right)$
$N_{St}\left(i_{st}\right), N'_{St}\left(i'_{st}\right)$	Probabilistic sequence of planed/updated N_s at time t
$\Delta N'_t\left(i_t\right)$	Probabilistic sequence of the number of remaining available batteries
f_{under}	The undervalued part of electricity cost
λ_{dns},λ_{under}	The unit penalty for not meeting the swapping demand / the underestimation of electricity cost

I. INTRODUCTION

As an important solution to urban environmental problems, electric vehicles (EVs) have attracted extensive attention from governments, academia and industry worldwide in recent years [1], and been vigorously promoted. In order to promote the implementation of the Paris Agreement, France, Germany, Norway, Netherland and other European countries agreed, during the 2017 G20 meeting in Hamburg, to ban the automobile running on fuels between 2025 and 2040. The announcement largely accelerates the development of battery in EV with its application. For buses and Taxi which have longer operation time than parking time and unified battery models, the battery swapping should enable the rapid battery energy replenishment. Besides, by managing the battery charging strategy, battery swapping could be considered as the most efficient alternative mode: 1) eliminate the peak-to-valley load difference 2) adjust the grid frequency 3) reduce the energy cost 4) increase the asset utilization efficiency [2]–[7]. The facilities to realize the battery swapping mode usually occupy a large area. If large-scale PV power generation can be arranged according to local conditions, the proportion of clean energy in the primary energy of EVs can be more effectively increased, and the power supply burden of the utility grid can be reasonably reduced [8]. Obviously, the economic scheduling of an PV-based BSS plays a very important role in supporting the realization of the above effects.

The day-ahead economic scheduling of an PV-based BSS 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 [8]–[11]. Most studies have used the typical cases of uncertain factors to represent uncertainties. 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. So far, there is no day-ahead dispatching research of BSSs that can solve this problem.

For the mathematical model of the BSS day-ahead scheduling with uncertain factors, authors in [13] considered the uncertainty of swapping demand, and used the robust optimization method to design the BSS day-ahead scheduling. In fact, different operators have different risk appetite. However, the robust optimization results are relatively conservative and cannot meet the high-yield expectations of some operators. Thus, this paper adopts the chance-constrained programming with flexible choice of confidence level to establish the economic operation model of the BSS. The operation plan formulated according to the operator's risk appetite can realize the economic operation of the BSS at the given confidence level.

For the problem of solving the BSS scheduling model, the algorithm used to solve this problem is compared in [14], and the results show the superiority of GA in solving this type of problem. Therefore, GA is chosen to solve the model in this paper. In [15], 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 [16], 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 [18] has great guiding significance for the BSS operator to formulate the corresponding charging plan according to the grid operation requirements. According to the above literature review, the feasible solution space to the day-ahead scheduling can be constructed by using the battery load margin, and combined with GA to achieve optimal operation and high efficiency.

The main contributions of the paper are:

(1) In this paper, the probabilistic sequence is used to describe the dual uncertainties of swapping demand and PV output, 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.

(2) The chance-constrained programming is adopted to establish the economic operation model of the BSS. Compared with the relatively conservative robust optimization, the proposed model can formulate the operation plan according to the operator's risk appetite, so as to meet the needs of different operators. In order to evaluate the solution quality and analyze the relationship between economy and risk, a risk assessment method based on the probabilistic sequence for day-ahead scheduling solutions is proposed.

(3) By using the controllable load margin of batteries in the BSS proposed in [17] to determine the feasible solution space, a fast optimization method for the BSS day-ahead scheduling model is proposed.

The rest of the paper is organized as follows: Section II describes the model of day-ahead scheduling for the BSS based on chance-constrained programming. In Section III, uncertain factors are described by using probabilistic sequences, and a chance constraints processing method based on probabilistic sequence is proposed to achieve deterministic transformation of chance constraints. Then the fast optimization method based on determining feasible solution space is proposed in Section IV. In Section V, risks in day-ahead scheduling for the BSS are described, and a risk assessment method for day-ahead scheduling solutions is proposed to evaluate the solution quality. In Section VI, case studies are described and the assigned values for related parameters are given. In addition, case comparisons are conducted and results are analyzed. Conclusions of the paper are made in Section VII followed by references.

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

Since the day-ahead scheduling makes decisions before observing uncertain factors, it is difficult to coordinate uncertain factors with traditional deterministic planning methods. The chance-constrained programming could well describe the uncertainty of stochastic variables so that the decision can realize the economic operation of the BSS at the given confidence level. Therefore, the chance-constrained programming is used to construct the day-ahead scheduling model of the BSS.

A. CHANCE-CONSTRAINED PROGRAMMING

Chance-constrained programming allows the decision to fail to satisfy the constraints under a certain probability, but the decision should make the probability that the constraints be satisfied is not lower than the confidence level. Chance-constrained programming can be expressed as follows:

$$\begin{cases} \min \bar{f} \\ s.t. H_j(x) \leq 0, & j = 1, 2, \cdots m \\ \quad P_r\{G_k(x, \xi) \leq 0\} \geq \alpha, & k = 1, 2, \cdots p \\ \quad P_r\left\{f(x, \xi) \leq \bar{f}\right\} \geq \beta \end{cases} \tag{1}$$

where x indicates the decision vector, ξ indicates the stochastic parameter vector, $H_j(x)$ is the traditional deterministic constraint, $G_k(x, \xi)$ is the chance constraint, $f(x, \xi)$ indicates the objective function, $P_r\{\cdot\}$ indicates the probability of the event being established, α and β are confidence levels preset by the decision maker, $\bar{f}$ is the minimum value taken by the objective function $f(x, \xi)$ when the confidence level is not lower than β.

B. OBJECTIVE FUNCTION

In order to minimize the cost of electricity purchased from the utility grid, the uncertainties of swapping demand and PV power generation during the operation of the BSS are considered when the initial charging time of batteries is optimally arranged to achieve the most economic operation of the BSS. The objective function is shown in equation below:

$$\min F = \sum_{t=1}^{24} P_{EL}(t)\, p(t) \tag{2}$$

where,

$$P_{EL}(t) = \begin{cases} P_b(t) - P_{PV}(t) & P_b(t) \geq P_{PV}(t) \\ 0 & P_b(t) < P_{PV}(t) \end{cases} \tag{3}$$

where $P_{EL}(t)$ indicates equivalent charging load. $P_b(t)$ indicates the charging load of batteries in the BSS during the t-th period, that is, the decision variable of the day-ahead scheduling of the BSS. $P_{PV}(t)$ indicates the PV output power in the t-th period, which is a stochastic variable; $p(t)$ indicates the grid time-of-use (TOU) price.

C. CONSTRAINTS

1) CHANCE CONSTRAINT OF SWAPPING DEMAND SATISFACTION

During the actual operation of the BSS, the swapping demand varies due to the error from day-ahead PV generation forecast. In order to ensure that the probability of the actual swapping demand satisfaction is not lower than the given confidence level α, the following chance constraint is set.

$$P_r\{N_{need}(t) \leq N_s(t)\} \geq \alpha \tag{4}$$

where $N_{need}(t)$ is a stochastic variable, representing the actual swapping demand for the t-th period. $N_s(t)$ is the number of batteries that the BSS plan to provide for t-th period.

2) CHANCE CONSTRAINT OF ELECTRICITY COST

Affected by the forecasting error of PV output, the cost generated in the actual operation of the day-ahead scheduling scheme is volatile. The probability that the electricity cost of the day-ahead scheduling plan for the actual operation does not exceed the objective value should not be lower than the given confidence level β.

$$P_r\left\{f(P_b, P_{PV}) \leq \bar{f}\right\} \geq \beta \tag{5}$$

where $f(P_b, P_{PV})$ indicates electricity cost function. P_b is the decision vector, that is, the load of charging batteries in each period set by the day-ahead scheduling. P_{PV} is a stochastic vector. $\bar{f}$ is the minimum value taken by electricity cost function when the confidence level is not lower than β.

3) BATTERIES CHARGING LOAD DETERMINISTIC CONSTRAINT

In this paper, the deterministic constraint on the batteries charging load is shown in equation below:

$$P_{\min}(t) \leq P_b(t) \leq P_{\max}(t) \tag{6}$$

where $P_{\min}(t)$ and $P_{\max}(t)$ are the upper and lower limits of the charging load margin of the batteries proposed in [17] after considering the swapping demand.

III. CHANCE CONSTRAINTS PROCESSING METHOD BASED ON PROBABILISTIC SEQUENCES

Traditional chance-constrained programming is mostly solved by stochastic simulation methods, but the result of each simulation is different. It is difficult to obtain the inverse function of the cumulative distribution function (CDF) of stochastic variables when the chance constraint is transformed into a deterministic equivalent form. In order to solve the above problems, the probabilistic sequence is used to describe uncertainties of both the swapping demand and the PV output, then sequence operation is performed on the objective function containing stochastic variables to obtain the calculation result. This is also the result of the discretization of the probability distribution of the daily electricity cost. This allows chance constraints to be transformed into a deterministic constraint by using the discretized probability distribution.

A. PROBABILISTIC SEQUENCE AND ITS OPERATION THEORY

The existence of uncertainty makes the real problem more complicated and difficult. The academic community has proposed a variety of analytical methods to solve the uncertainty problem. In [18], probabilistic sequences are defined on the basis of the general sequence operation, and the probabilistic sequence is used to represent the probability distribution of stochastic variables, which is used to deal with complex uncertainties in reality problem [19]. The nature of its operation is discussed in detail in [20].

In [20], the probabilistic sequence is defined as: a discrete sequence $a(i)$ with known length N_a, if it satisfies: $0 \leq a(i) \leq 1$ 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

$$x(i) = \sum_{i_a+i_b=i} a(i_a)\, b(i_b) \quad i = 0, 1, \cdots, N_x \tag{7}$$

where $N_x = N_a + N_b$. The operation defined by "(7)" 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

$$x(i) = a(i_a) \oplus b(i_b) \tag{8}$$

2) SUBTRACTION-TYPE CONVOLUTION OPERATION

$$y(i) = \begin{cases} \sum\limits_{i_a-i_b=i} a(i_a)\, b(i_b) & 1 \leq i \leq N_y \\ \sum\limits_{i_a\leq i_b} a(i_a)\, b(i_b) & i = 0 \end{cases} \tag{9}$$

where $N_y = N_a$. The operation defined by "(9)" is the subtraction-type convolution operation. The sequence $y(i)$ of length N_y is the subtraction-type convolution operation sequence of $a(i_a)$ and $b(i_b)$, which can be denoted as

$$x(i) = a(i_a)\, \Theta b(i_b) \tag{10}$$

3) SEQUENCE MULTIPLICATION OPERATION

$$y(i) = \begin{cases} \sum\limits_{i_a-i_b=i} a(i_a)\, b(i_b) & 1 \leq i \leq N_y \\ \sum\limits_{i_a\leq i_b} a(i_a)\, b(i_b) & i = 0 \end{cases} \tag{11}$$

where $N_s = N_a N_b$. The operation defined by "(11)" 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

$$s(i) = a(i_a) \circledcirc b(i_b) \tag{12}$$

B. PROBABILISTIC SERIALIZATION MODEL FOR STOCHASTIC VARIABLES

In this section, probabilistic serialization models for stochastic variables are constructed according to the probability density function (PDF) of stochastic variables. This method is suitable for various types of stochastic variables. In this paper, the stochastic variables are assumed to follow the normal distribution.

1) PROBABILITY SERIALIZATION MODEL FOR 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,

$$P_{PVr}(t) = P_{PVf}(t) + e(t) \tag{13}$$

The predicted error $e(t)$ is assumed to follow a normal distribution $N\left(0, \sigma_{PV,t}^2\right)$, where the standard deviation $\sigma_{PV,t}$ is 10% of the predicted value $P_{PVf}(t)$. The predicted value is used as the mean value to construct the probability density function of PV output. And the corresponding PDF at time t is shown as equation below:

$$f_{PV,t}(x) = \frac{1}{\sqrt{2\pi}\,\sigma_{PV,t}} \exp\left(-\frac{\left(x - P_{PVf}(t)\right)^2}{2\sigma_{PV,t}^2}\right) \tag{14}$$

The time-series multi-state probability sequence of PV output $P_{PV,t}(i_{PVt})$ is constructed by using the PDF of PV output. The length $N_{PV,t}$ of the sequence $P_{PV,t}(i_{PVt})$ is

$$N_{PV,t} = \left[P_{PV,t\max}/\Delta P\right] \tag{15}$$

where $\left[P_{PV,t\max}/\Delta P\right]$ is the largest integer below $P_{PV,t\max}/\Delta P$. $P_{PV,t\max}$ is the maximum possible value of PV output in t-th period. ΔP is the discretization step size. The probability serialization model for PV generation is given by

$$P_{PV,t}\left(i_{PVt}\right)=\begin{cases}\int_0^{\frac{\Delta P}{2}} f_{PV,t}\left(x\right)dx & i_{PVt}=0\\ \int_{i_{PVt}\Delta P-\frac{\Delta P}{2}}^{i_{PVt}\Delta P+\frac{\Delta P}{2}} f_{PV,t}\left(x\right)dx & 0<i_{PVt}<N_{PV,t}\\ \int_{i_{PVt}\Delta P-\frac{\Delta P}{2}}^{i_{PVt}\Delta P} f_{PV,t}\left(x\right)dx & i_{PVt}=N_{PV,t}\end{cases} \tag{16}$$

where $P_{PV,t}\left(i_{PVt}\right)$ represents the probability of different PV output states at time t.

2) PROBABILITY SERIALIZATION MODEL FOR SWAPPING DEMAND

There is great uncertainty in the travel of EV users, which leads to the fluctuation of swapping demand. In [17], according to the distribution function of the total mileage of EVs and the proportion of mileage in each period, the Monte Carlo method is used to simulate the probability that each EV needs to be charged at each period, so as to simulate the number of swapping demand in each period. Considering the randomness of Monte Carlo simulation and the uncertainty of actual swapping demand, the simulation error is added to the swapping demand model in this paper. Similarly, the simulation error is assumed to follow a normal distribution $N\left(0,\sigma_{need,t}^2\right)$, where the standard deviation $\sigma_{need,t}$ is 10% of the simulation value. The results obtained by Monte Carlo simulation in [17] are used as the mean value to construct the PDF for swapping demand. And the corresponding PDF at time t is shown as equation below:

$$f_{need,t}\left(x\right)=\frac{1}{\sqrt{2\pi}\sigma_{need,t}}\exp\left(-\frac{\left(x-N_{need,t}\right)^2}{2\sigma_{need,t}^2}\right) \tag{17}$$

In the same way, the probability serialization model for swapping demand is given by

$$N_{need,t}\left(i_{Nt}\right)=\begin{cases}\int_0^{\frac{1}{2}} f_{need,t}\left(x\right)dx & i_{Nt}=0\\ \int_{i_{Nt}-\frac{1}{2}}^{i_{Nt}+\frac{1}{2}} f_{need,t}\left(x\right)dx & 0<i_{Nt}<N_{Nneed,t}\\ \int_{i_{Nt}-\frac{1}{2}}^{i_{Nt}} f_{need,t}\left(x\right)dx & i_{Nt}=N_{Nneed,t}\end{cases} \tag{18}$$

where $N_{need,t}\left(i_{Nt}\right)$ represents the probability of different swapping demand value at time t. The discretization step size of $f_{need,t}\left(x\right)$ is 1. The length of the sequence $N_{need,t}\left(i_{Nt}\right)$ is $N_{Nneed,t}$, and $N_{Nneed,t}$ is the maximum value of the swapping demand at time t.

C. SEQUENCE OPERATION RESULTS OF THE OBJECTIVE FUNCTION

According to the above equations, the time series probabilistic sequence $P_{PV,t}\left(i_{PVt}\right)$ of PV output in the t-th period is obtained, and the sequence length is $N_{PV,t}$. $P_{b,t}\left(i_{bt}\right)$ is the unit sequence of the charging load of batteries in the t-th period. The sequence length is $N_{b,t}$.

$P_{EL,t}\left(i_{ELt}\right)$ indicates that the probabilistic sequence of the equivalent charging load in the BSS during the t-th period. The sequence length is $N_{EL,t}$, then $P_{EL,t}\left(i_{ELt}\right)$ is the subtraction-type convolution operation sequence of $P_{PV,t}\left(i_{PVt}\right)$ and $P_{b,t}\left(i_{bt}\right)$, where $N_{EL,t}=N_{PV,t}$. According to the definition of sequence operation:

$$P_{EL,t}\left(i_{ELt}\right)=\begin{cases}\sum\limits_{i_{bt}-i_{PVt}=i_{ELt}} P_{b,t}\left(i_{bt}\right)P_{PV,t}\left(i_{PVt}\right) & 1\le i_{ELt}\le N_{EL,t}\\ \sum\limits_{i_{bt}\le i_{PVt}} P_{b,t}\left(i_{bt}\right)P_{PV,t}\left(i_{PVt}\right) & i_{ELt}=0\end{cases} \tag{19}$$

$C_t\left(i_{Ct}\right)$ is the probabilistic sequence of the electricity purchase cost of the BSS, and the sequence length is N_{Ct}.$p_t\left(i_{pt}\right)$ is the unit sequence of the TOU price, which has the sequence length of N_{pt}, where $N_{pt}=\left[p\left(t\right)/\Delta p\right]$. Δp indicates the discretization step size of the TOU price. Then $C_t\left(i_{Ct}\right)$ is the sequence multiplication operation result of $P_{EL,t}\left(i_{ELt}\right)$ and $p_t\left(i_{pt}\right)$. According to the definition of sequence operation:

$$C_t\left(i_{Ct}\right)=\begin{cases}\sum\limits_{i_{Ct}=i_{ELt}\cdot i_{pt}} P_{EL,t}\left(i_{ELt}\right)p_t\left(i_{pt}\right) & i_{Ct}=i_{ELt}i_{pt}\\ 0 & i_{Ct}\neq i_{ELt}i_{pt}\end{cases} \tag{20}$$

where $i_{Ct}=0,1,\cdots,N_{Ct}, N_{Ct}=N_{EL,t}\cdot N_{pt}$∘

Equation (21) indicates the probabilistic sequence of electricity cost of the BSS for a full-day. The sequence length is N_F, which is calculated from the $C_t\left(i_{Ct}\right)$ volumes of 24 time periods:

$$F\left(i_F\right)=\sum_{i_{C1}+i_{C2}+\cdots+i_{C24}=i_F}\left(\prod_{t=1}^{24} C_t\left(i_{Ct}\right)\right) \tag{21}$$

where, $i_F=0,1,\cdots,N_F, N_F=\sum\limits_{t=1}^{24} N_{Ct}$.

Since the probability serialization of the probability distribution of stochastic variables is carried out in this paper, the final optimization result is affected by the value of the discretization step size. Smaller discretization steps can achieve higher computational accuracy, but may cause problem that the probabilistic sequence is too long.

Considering that the charging load of the BSS is a multiple of the average charging power of the battery, and it needs to perform the subtraction-type convolution operation with the probability sequence of the PV output, the discretization step size of the two probability sequences is taken as the average charging power of the battery. At the same time, since the value of the swapping demand is a non-negative integer, the discretization step size is set as 1. For the above probabilistic sequence, the currently selected discretization step size is the physical minimum value, so there is no need to continue to reduce the discretization step size.

In addition, as the discretization step size decreases, the probabilistic sequence length of stochastic variables increases sharply, resulting in a sharp increase in computation time. Therefore, it is of little significance to continue to reduce the step size to improve the accuracy. Therefore, for the TOU price as a unit sequence, the discretization step size is set to 0.1.

D. DETERMINISTIC TRANSFORMATION OF CHANCE CONSTRAINTS

The timing multi-state probability sequence $N_{need,t}(i_{Nt})$ for swapping demand has been constructed above. The possible swapping demand at time t is divided into $N_{Nneed,t}+1$ states, and the probability corresponding to each state is

$$P\left\{N_{need,t}=i_{Nt}\right\}=N_{need,t}\left(i_{Nt}\right) \tag{22}$$

where, $i_{Nt}=0,1,\cdots,N_{Nneed,t}$.

Then, the cumulative distribution function (CDF) of swapping demand at time t is

$$F_{N_{need,t}}(x)=P\left\{N_{need,t}\leq x\right\}=\sum_{i_{Nt}=0}^{x}N_{need,t}\left(i_{Nt}\right) \tag{23}$$

where, $x=0,1,\cdots,N_{Nneed,t}$.

In order to satisfy the chance constraint in "(4)," it is assumed that the number of available batteries at time t in the BSS is $N_s(t)$. Then $N_s(t)$ should satisfy:

$$N_s(t)\geq\min\left\{x|F_{N_{need,t}}(x)\geq\alpha\right\} \tag{24}$$

Equation (24) indicates that the probability that the number of available batteries in the BSS can meet the swapping demand is not lower than α at time t. Therefore, it is equivalent to "(4)".

Similarly, the CDF of the electricity cost can be obtained, which is represented by $F_f(x)$. The deterministic equivalent form of "(5)" can be expressed as follows:

$$\bar{f}\geq\min\left\{x|F_f(x)\geq\beta\right\} \tag{25}$$

IV. FAST OPTIMAIZATION METHOD BASED ON DETERMINING FEASIBLE SOLUTION SPACE

In this paper, since the equivalent forms of chance constraints are nonlinear, the optimization problem of the BSS day-ahead scheduling model is nonlinear optimization problem (NLP). GA was inspired by the process of natural selection such as mutation and crossover, so that it is commonly applied on solving the optimization and search problems. Therefore, GA is chosen to solve the model in this paper.

In the BSS day-ahead scheduling model, charging plan is the decision variable. If the total capacity of chargers in the BSS is the solution space, the problems of large solution space and slow convergence speed might appear. In [17], considering the swapping demand and the operation state of the BSS, the recursive concept is used to obtain the controllable load margin band of batteries. The load margin of batteries in the BSS is used as the optimization space for day-ahead scheduling. The method can avoid infeasible solutions, reduce optimization space, and improve the optimization efficiency of GA.

A. DETERMINATION OF LOAD MARGIN OF BATTERIES IN BSS

In [17], according to the state parameters of the batteries in the BSS, the state of the battery is represented by a three-dimensional row vector. The state matrix of the battery pack is established,

$$Status=(n,SocN,T_s) \tag{26}$$

where n is the identifier of the current state of charge:

$$n=\begin{cases}1 & \text{charging state}\\ 0 & \text{waiting state}\end{cases} \tag{27}$$

$SocN$ is the current state of battery. SOC_{max} is the amount of charge when the battery is fully charged. The state of charge at the end of charging is SOC_{max}. T_S indicates the moment when the battery is replaced, i.e, the starting time when battery can be charged.

According to the above battery state matrix, the controlled state of the backup battery in the BSS can be divided into four types: a) The batteries being charged (the number is N_1), b) The batteries that must be stopped charging (the number is N_2), c) Fully charged batteries (the number is N_3), d) The batteries to be charged (the number is N_4). The first three types of batteries are in an uncontrollable state. In order to meet the swapping demand at the subsequent time, a portion of the battery pack to be charged must be charged at each time. The N_{4-1} amount of batteries is in an uncontrollable state and the remaining N_{4-2} amount of batteries will be charged are in a controllable state.

According to the definition of various states of the batteries, the state vectors corresponding to the various state batteries can be expressed as:

$$\begin{cases}Status_1=(1,SocN,T_s) & \text{st: } 0<\text{SocN}<\text{SOC}_{\max}\\ Status_2=(1,SocN,T_s) & \text{st:SocN}=\text{SOC}_{\max}\\ Status_3=(0,SocN,T_s) & \text{st:SocN}=\text{SOC}_{\max}\\ Status_4=(0,SocN,T_s) & \text{st: } 0<\text{SocN}<\text{SOC}_{\max}\end{cases} \tag{28}$$

The probability distribution of the initial charge amount $SocN$ of the batteries swapped in each period is referred to [17]. The battery load margin of the t+1 period is affected by the charging load of the batteries during the t period and the swapping demand during the t+1 period. Therefore, it can be estimated by the battery state information of the t period and the t+1 period [17].

$$\begin{cases}P_{\min}(t+1)\leq P_b(t+1)\leq P_{\max}(t+1)\\ P_{\min}(t+1)=P_{rated}*[N_1(t)-N_2(t+1)+N_{4-1}(t+1)]\\ \qquad=P_b(t)+P_{rated}*[N_{4-1}(t+1)-N_2(t+1)]\\ P_{\max}(t+1)=P_{rated}*[N_1(t)-N_2(t+1)\\ \qquad+N_{4-1}(t+1)+N_{4-2}(t+1)]\\ \qquad=P_b(t)+P_{rated}*[N_4(t+1)-N_2(t+1)]\\ \qquad=P_b(t)+P_{rated}*[N_{left}(t)+N_{need}(t+1)\\ \qquad-N_2(t+1)]\end{cases} \tag{29}$$

where $N_{left}(t)$ indicates the number of batteries to be charged in the t period. $N_{need}(t+1)$ is the swapping demand obtained by Monte Carlo simulation in [17].

In this paper, given the uncertainty of swapping demand, in order to make the probability that the actual swapping demand is met not lower than the given confidence level, $N_{need}(t+1)$ in "(29)" is replaced by the number of batteries $N_S(t+1)$ that the BSS planned to provide for swapping.

B. THE SOLVING PROCESS BASED ON GA

In this paper, the real-coded GA is combined with the sequence operation to optimize the charging plan of the batteries to obtain the minimum electricity cost that meets the chance constraints considering the uncertainty.

1) THE SELECTION OF DECISION VARIABLE IN THE GA

Refer to "(29)," the upper and lower limits of the batteries load margin in the BSS are affected by the charging load $P_b(t)$ from the previous time. The $P_b(t)$ throughout the day is the decision variable in the economic operation model. The feasible solution space for the batteries charging plan is a variable and it is not convenient to solve. Therefore, the decision variable in the GA is set to 24 stochastic numbers $x(t)$ between [0, 1], which represents the position of the charging load in the feasible solution space.

$$P_b(t) = P_{\min}(t) + x(t)\left(P_{\max}(t) - P_{\min}(t)\right) \tag{30}$$

2) THE SOLVING PROCESS

The specific process of using GA to solve the economic operation model of the BSS can be divided into the following three steps, as shown in Fig. 1.

Step 1: Input TOU electricity price and construct probabilistic sequences of variables. In addition, initialize GA parameters and population.

Step 2: The fitness value in each iteration is calculated. Calculate the probabilistic sequence of electricity cost throughout the day. Find the minimum value $\bar{f}$ taken by the objective function when the confidence levels are satisfied. The fitness function is $1/\bar{f}$.

Step 3: If the termination condition are satisfied, output the charging plan and the minimum value of electricity cost for the BSS; otherwise, perform genetic operation and go to step2. According to the varied population genetic algorithm proposed in [14], the population size at different stages was adjusted in genetic operation to improve algorithm performance.

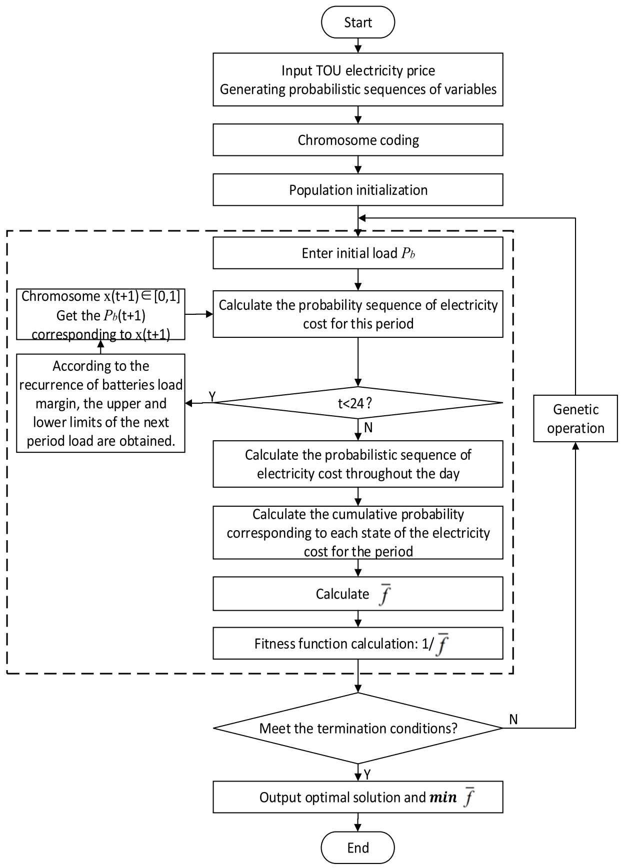


FIGURE 1. GA solution flow chart.

V. RISK ANALYSIS AND QUALITY EVALUATION OF DAY-AHEAD SCHEDULING SOLUTIONS

Since the chance constraints in the model are satisfied at certain probability, there must be a case that the chance constraints are not satisfied, which could cause the underestimation of the electricity cost or unsatisfied swapping demand. In order to justify the feasibility of the day-ahead scheduling solutions and evaluate its quality, the economics and risks of the day-ahead scheduling solutions are thoroughly demonstrated in this section. A risk assessment method based on the probabilistic sequence for day-ahead scheduling solutions is proposed, and the penalty cost corresponding to the risk is calculated to evaluate the solution quality.

A. RISK OF UNMET SWAPPING DEMAND

The swapping demand constraint in "(4)" would not satisfied when the swapping demand is greater than the number of batteries that the BSS can provide for swapping, and the swapping demand of some users cannot be satisfied. This situation reduces the user satisfaction, which is not desirable for the BSS operator. Therefore, this paper quantifies the risk when the swapping demand is not met, and calculates the corresponding penalty cost when the situation occurs. At the same time, the swapping demand may also be lower than the number of batteries that the BSS plans to provide for swapping. Therefore, under the premise of taking user's satisfaction into account, the following rules for the actual operation of the BSS 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.

$N_s'(t)$ represents the number of available batteries in the BSS after the update,

$$N_s'(t+1) = \begin{cases} N_s(t+1) + \left[N_s'(t) - N_{need}(t)\right], & N_{need}(t) \le N_s'(t) \\ N_s(t+1), & N_{need}(t) > N_s'(t) \end{cases} \tag{31}$$

Equation (32) is the number of EVs that fail to swap during the t-th period:

$$D_{NS}(t) = \begin{cases} N_{need}(t) - N_s'(t) & N_{need}(t) > N_s'(t) \\ 0 & N_{need}(t) \le N_s'(t) \end{cases} \tag{32}$$

In this paper, the expected value is used to represent the unmet swapping demand during the t-th period. Penalty cost corresponding to the risk is shown in equation below:

$$C_{DNS} = \sum_{t=1}^{24} E(D_{NS}(t)) \lambda_{dns} \tag{33}$$

where λ_{dns} indicates the unit penalty of the BSS for not meeting the swapping demand

According to the actual operation rules of the BSS, the corresponding probabilistic sequence of the number of available batteries in the BSS at the updated time t-th period is denoted as $N_{St}'(i_{st}')$, and its sequence length is N_{Nst}'. The probabilistic sequence corresponding to the number of remaining full-charged batteries in the t-th period is denoted as $\Delta N_t'(i_t)$, and the sequence length is $N_{\Delta Nt}$.

$$\Delta N_t'(i_t) = N_{St}'(i_{st}') \Theta N_{need,t}(i_{Nt}) \tag{34}$$

where $i_t = 0, 1, \cdots, N_{\Delta Nt}, N_{\Delta Nt} = N_{Nst}'$.

The probabilistic sequence corresponding to the number of batteries that the BSS originally planned to provide for the t+1 time period is denoted as $N_{S(t+1)}(i_{s(t+1)})$, and the sequence length is $N_{Ns(t+1)}$. Probabilistic sequence corresponding to the number of available batteries after the t+1 period update is sequence $N_{S(t+1)}'\left(i_{s(t+1)}'\right)$, and its sequence length is $N_{Ns(t+1)}'$.

$$N_{S(t+1)}'\left(i_{s(t+1)}'\right) = N_{S(t+1)}\left(i_{s(t+1)}\right) \oplus \Delta N_t(i_t) \tag{35}$$

where $i_{s(t+1)}' = 0, 1, \cdots, N_{Ns(t+1)}', N_{Ns(t+1)}' = N_{Ns(t+1)} + N_{\Delta Nt}$.

The probabilistic sequence of the unmet swapping demand in the t-th period is denoted as $D_{NSt}(i_{Dt})$, and its sequence length is N_{Dt},

$$D_{NSt}(i_{Dt}) = N_{need,t}(i_{Nt}) \Theta N_{St}'(i_{st}') \tag{36}$$

where $i_{Dt} = 0, 1, \cdots, N_{Dt}, N_{Dt} = N_{Nneed,t}$.

The expected value of the unmet swapping demand during the t-th period:

$$E(D_{NS}(t)) = \sum_{i_{Dt}=0}^{N_{Dt}} i_{Dt} D_{NSt}(i_{Dt}) \tag{37}$$

By substituting in "(33)" the penalty cost of the unmet swapping demand can be obtained.

B. RISK OF UNDERESTIMATION OF COSTS

Affected by the forecasting error of PV output, it is inevitable that "(5)" is not satisfied so that there is a risk of underestimation of the electricity cost.

$$C_{under} = E(f_{under}) \lambda_{under} \tag{38}$$

where $E(f_{under})$ is the expected value of the under-estimated part. λ_{under} is the unit penalty for the underestimation of electricity cost in day-ahead scheduling.

Record the undervalued part of electricity cost as $f_{under}(i_F)$,

$$f_{under}(i_F) = \begin{cases} 0 & i_F \Delta P \Delta p \le \min \bar{f} \\ i_F \Delta P \Delta p - \min \bar{f} & i_F \Delta P \Delta p > \min \bar{f} \end{cases} \tag{39}$$

where ΔP is the discretization step size of the PV output, Δp is the discretization step size of the TOU price.

$$E(f_{under}) = \sum_{i_F}^{N_F} f_{under}(i_F) F(i_F) \tag{40}$$

By substituting "(40)" into "(38)", the penalty cost corresponding to the underestimation can be obtained.

C. THE PENALTY COST CORRESPONDING TO THE RISK OF DAY-AHEAD SCHEDULING

The risk of making decisions for the day-ahead scheduling is determined by the stochastic variables and the confidence levels chosen by the BSS operator. The penalty cost corresponding to this risk consists of the above two penalty costs,

$$C_{risk} = C_{DNS} + C_{under} \tag{41}$$

VI. CASE STUDY

A. ASSUMPTIONS AND SIMULATION DATA SETTING

A PV-based battery swapping station in the city is selected as the research object. 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 of purchase electricity from the utility grid refer to the data in [16].

The PV installation capacity of the BSS is 240 kW. The typical PV output data is selected as the PV output prediction parameter. The discretization step size is 2.5 kW. The multi-state probability sequence of the constructed PV output timing is shown in Fig. 2, which represents the probability of different values in each period.

According to the swapping demand in [17], the timing multi-state probabilistic sequence of swapping demand is constructed as the mean value, as shown in Fig. 3. The graph represents the probability corresponding to different value of swapping demand in each period.

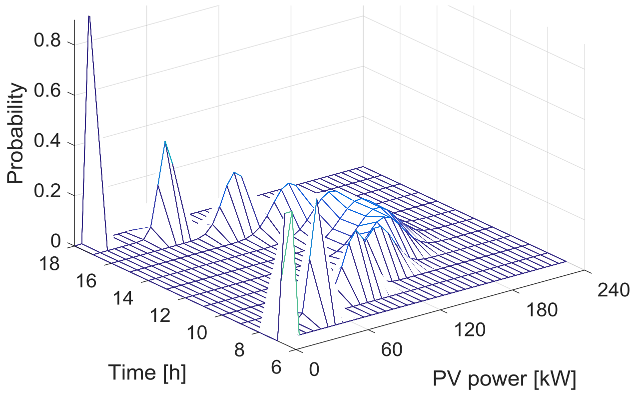


FIGURE 2. Time-series multi-state probabilistic sequence of PV output.

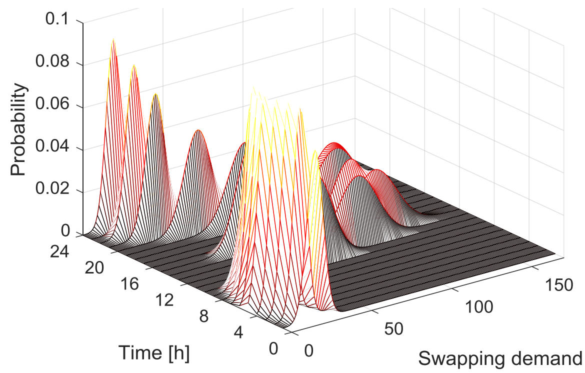
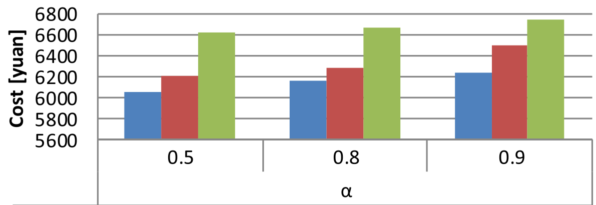


FIGURE 3. Time- series multi-state probabilistic sequence of swapping demand.



	0.5	0.8	0.9
β 0.9	6043.5	6154.4	6232.1
β 0.95	6195.9	6276.1	6497.6
β 0.99	6616.6	6668.7	6743.2

FIGURE 4. The cost of electricity purchased from the utility grid at different confidence levels.

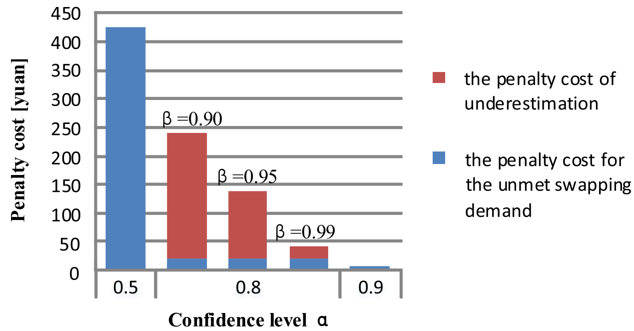


FIGURE 5. Penalty cost at different confidence levels.

B. EVALUATION OF DAY-AHEAD SCHEDULING SOLUTIONS

In this section, the economics and risk of the solutions obtained under different satisfactions are analyzed to evaluate the solution quality, and the impact of different confidence levels on the solutions is analyzed. The risk penalty cost of day-ahead solutions in actual operation is obtained according to the risk assessment method in section V.

1) ECONOMIC AND RISK ANALYSIS

The confidence level in the economic operation model of the BSS proposed in this paper is set by the BSS operator according to their own risk appetite. The electricity cost and the risk penalty cost corresponding to day-ahead scheduling solutions are affected by the choice of the confidence level. The study on different confidence levels α and β is set below and the results are compared in Fig. 4.

A comparison of the penalty cost for the unmet swapping demand corresponding to the solutions developed under different confidence levels α and the penalty cost corresponding to the cost underestimation risk for different β when the α equals to 0.8 are shown in Fig. 5.

It can be seen from Fig. 4 and Fig. 5 that the higher the confidence level, the more electricity cost for the corresponding solution. However, after the risk assessment of the solution, it can be seen that the risk penalty cost is lower with the higher confidence level, indicating that the user satisfaction and the feasibility of the solution are higher. The solution with a lower confidence level, which has lower estimated electricity costs. However, the risk assessment results show that the risk penalty cost is higher, indicating that the solution has lower user satisfaction and lower feasibility.

Reasons for the above results are as follows: In case of complying with the actual operating rules of the BSS, the penalty cost for not meeting the swapping demand is related to the confidence level α. The larger α, the greater the probability that the swapping demand will be satisfied. With higher confidence level β, the risk of cost underestimation is lower, and the impact of PV output uncertainty on the actual operation of day-ahead scheduling solutions is smaller. The higher confidence level means that the solution takes into account more comprehensive uncertainty, and it will also cause a certain degree of economic loss while improving the applicability of the solution to uncertainty.

By analyzing the economy and risk of the day-ahead scheduling solutions, we can evaluate the solution quality, so as to provide guidance for operators with different risk appetite.

2) THE IMPACT OF CONFIDENCE LEVEL β ON DAY-AHEAD SCHEDULING SOLUTIONS

Considering user satisfaction, the BSS operator can set different confidence levels (β) according to their own risk appetite

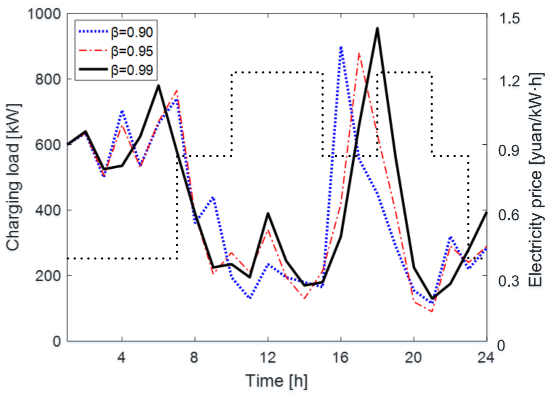


FIGURE 6. Charging plan at different confidence levels.

based on the uncertainty of PV output, as a result, corresponding charging plan can be formulated.

The swapping demand model obtained by Monte Carlo simulation is used as the predicted value to construct the swapping demand uncertainty model. When $\alpha = 0.8$, the charging plan formulated with different β is shown in Fig. 6. With respect to Fig. 6, when the confidence level of the swapping demand is determined, battery charging load in the daytime declines if the charging peak on 7am is shifted to an earlier period and charging peak on 6pm is shifted to a later period, comparing the charging plan with larger β with that with smaller β. And then the impact of uncertainty of PV output on day-ahead scheduling is weakened and the confidence level of day-ahead scheduling is improved.

Charging plans at different confidence levels can make a sensitive response to the change of TOU price. During the time period before the electricity price rises at 7am. and 6pm, each charging plan will charge the battery in advance to different degrees, and reduce the number of charging batteries in the period after the electricity price rises. In addition, although the economic charging plan reserves the battery power in advance during the period when the electricity price is low, the high-price period around 12am and 6pm. will inevitably have different degrees of charging load peak due to the peak demand for charging. Since the charging plan of low electricity price before 12am reserve the battery power in advance, the charging peak at 12am is lower than that at about 6pm.

C. COMPARISON OF PROCESSING METHODS FOR UNCERTAIN FACTORS

This comparison shows whether the results will be improved if the probabilistic sequence is used, as shown in Table. 1. The probabilistic sequence and multi-scenario method are respectively adopted to deal with uncertain factors and formulate charging schemes.

Multi-scenario method is a method of representing uncertainties with a certain number of typical scenarios [21]–[23]. Typical scenarios are established with the corresponding probabilities by K-mean clustering algorithm based on the

TABLE 1. Costs of different cases.

Cases	Electricity cost (yuan)	The penalty cost (yuan)	Total cost (yuan)
multi-scene technique	6296.2	325.1	6621.3
probabilistic sequences	6276.1	58.6	6334.7

forecasted data of PV output and swapping demand [21]. The expected value of the objective function can be calculated by the probability-weighted average of typical scenarios.

By using probabilistic sequences, the charging plan formulated at $\beta = 0.95$ in Fig. 6. 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 results of the risk assessment for day-ahead scheduling solutions show that the penalty cost of the proposed method is much lower than that of multi-scenario method.

This is because the scenario reduction of multi-scenario method 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. This illustrates that the solutions obtained by using the probabilistic sequence method has a greater applicability and a higher tolerance to the change of the uncertain factors.

D. ANALYSIS OF ELECTRICITY COST PROBABILISTIC SEQUENCE

In order to analyze the influence of the uncertainty of PV output on the electricity cost, the charging plan formulated at $\beta = 0.95$ in Fig. 6 is selected. By applying the probabilistic sequence operation method introduced above, the probability sequence of electricity cost in each period involving PV output during the day is obtained. The probability density map of the probability sequence of electricity cost in each period is plotted, as shown in Fig. 7.

It can be seen from Fig. 7 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 0 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.

E. 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. 8.

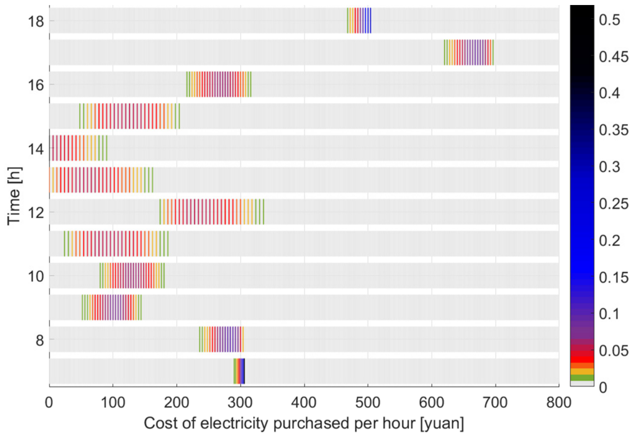


FIGURE 7. Probabilistic sequence of electricity purchase costs per hour.

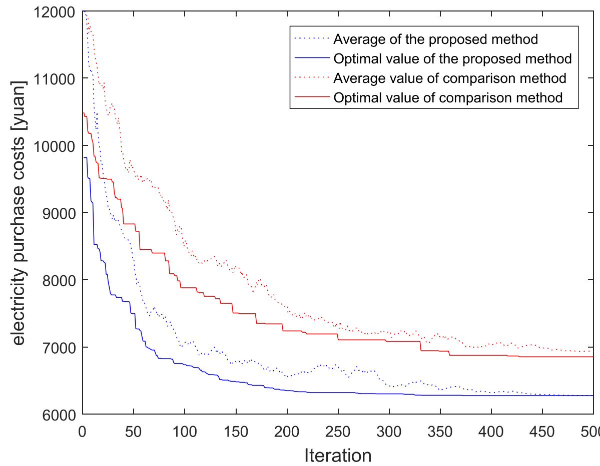


FIGURE 8. Evolutionary curves of different solution methods.

It can be seen from Fig. 8 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 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.

VII. 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 advanced chance-constrained programming is introduced into the economic operation model of the BSS. Compared with the conventional method, the advantages of using chance-constrained programming are analyzed, and the feasibility and effectiveness of this proposed method are validated. Besides, the risk brought by the confidence level selection in the actual operation in the BSS is studied which enables the BSS operators choosing the confidence level according to their own risk appetite. As a result, this paper provides guidance for the operators for a future reference.

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