Optimal V2G Method Considering Uncertainty of Distributed Generation and Load

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Abstract. The penetration of electric vehicles (EV) has brought many benefits to the active distribution network due to their unique advantages. But, EV also has negative impacts on the distribution network for their uncertainty. Moreover, the integration of distributed generation (DG) and the uncertainty of load demand also increase the negative impacts of EV on the distribution network. In this paper, optimal vehicle-to-grid (V2G) method considering uncertainty of distributed generation (DG) and load was proposed to reduce the negative impacts by minimizing the load peak-valley difference and maximizing the user economic benefits. To reduce the uncertainty of DG, we combined particle swarm optimization (PSO) and backpropagation neural network to create a prediction model to predict the output of DG. And Time-of-use (TOU) is used to optimize the load curve. Finally, the optimal charging and discharging time in a day can be obtained by improved particle swarm optimization algorithm (IPSO). The proposed method is verified by numerical analysis, which highlights that the proposed V2G scheduling can significantly improve distribution network stability and user economic benefits.

Keywords: Terms-V2G, Electric Vehicle, Distribution Network, Time-of-us.

1. Introduction

Nowadays the development of electric vehicles (EV) is more and more rapid [1]. The integration of EV to the distribution network can reduce the power loss and the difference between the peak and valley of the load, and decrease the pollution of environment. However, a high penetration of EV into the distribution network also can bring many technology challenge due to the uncoordinated and unbalanced charging /discharging of EV [2]. In order to reduce the negative impacts caused by the uncertainty of the user's charging/discharging behavior, the concept of vehicle-to-grid (V2G) that can effectively integrate EV into the distribution network has been proposed [3]. However, with the integration of distribution generation (DG) into the distribution network and the uncertainty of load, the V2G scheduling becomes more different.
Various studies have been carried out to reduce the adverse effects of EV charging/discharging on distribution network. There are two main ways to reduce the penetration of EV in distribution network by V2G. One is to directly upgrade the distribution network facilities to reduce the negative impact of EV [4-6]. Most of this kind of literatures focuses on dealing with the penetration of electric vehicles in the distribution network by planning charging stations [7]. However, the investors underestimate the influence of randomness of charging/discharging behavior on distribution network. This also makes the construction of the distribution network equipment not available for use.

Another way for easing the influence of high penetration of EV is by V2G scheduling to control EV uses behavior to shaving the peak [8]. A novel smart city modeling with combined EV traveling and charging network is formulated in [9] to alleviate the potential contingency brought by stochastic EV charging. Ref. [10] established a novel EV participation charging scheme for a decentralized blockchain-enabled smart grid system to minimize the power fluctuation level in the grid network and the overall charging cost for EV users. Two smart charging strategies was proposed by incorporating a unified G2V and V2G charging framework in [11] to study the impact on EV charging from an economic and a technical perspective. In order to solve the optimal scheduling of large-scale EV, ref. [12] proposed an economic dispatching model of microgrid to minimize the operating cost of microgrid and the cost of environment protection.

The above-mentioned research has good dispatching of EV through V2G, which enhances the stability of distribution network and increase the users economic benefits. However, most of them did not consider the influence of uncertainty of load and the integration of DG on V2G scheduling. In this paper, we proposed a novel model of optimal V2G method considering uncertainty of distributed generation and load for reducing the negative impact of EV penetration into a distribution network. Multi-objective was proposed to minimize the load peak-valley difference and maximize the users’ economic benefits. To deal with the DG integration and the uncertainty of load, particle swarm optimization (PSO) and backpropagation neural network algorithm (PSO-BP) is used to forecast DG and TOU is used to optimize load curve to reduce uncertainty. Finally, an improved particle swarm optimization algorithm (IPSO) was proposed to calculate the model to obtain the optimal scheduling of EV.

This paper is organized as follows. Section 2 briefly illustrates the methodology to reduce the uncertainty of load and deal with the integration of WG. The optimal V2G model is establish in Section 3. In section 4, we evaluate the proposed method by numerical analysis. Finally, the conclusion was draw in section 5.

2. Methodology of Reducing Uncertainty

This section mainly introduces the strategy of TOU to reduce load uncertainty and the PSO-BP algorithm to reduce wind power forecast error.

2.1. TOU Model of Load

There are many factors that affect load fluctuations, the most important of which is electricity price. As a special commodity, electric energy has the common characteristics of general commodities, and users’ demand and electricity price are generally inversely proportional [13]. The relationship between consumers and electricity price is usually expressed by the user elasticity coefficient. The coefficient is calculating using:

$$\delta = \frac{\partial l}{\partial p} = \frac{l_0}{p_0} \frac{dl}{dp}$$  \hspace{1cm} (1)

Where $l_0$ and $p_0$ are the load demand and electricity price before adopting TOU, respectively; $l$ and $p$ are current user load demand and electricity price, respectively.
 Considering the effect of time on the elastic coefficient, we found that the coefficient is different at different time, and can be divided into two cases,

\[
\begin{align*}
\delta_{ii} & = \frac{\Delta l_i}{\Delta p_i} \frac{p_i}{l_i} \\
\delta_{ij} & = \frac{\Delta l_j}{\Delta p_j} \frac{p_j}{l_j}
\end{align*}
\] (2)

Where $\delta_{ii}$ and $\delta_{ij}$ are self-elasticity coefficient and mutual-elasticity coefficient, respectively; $\Delta l_i$ is the load change at time $t_i$; $\Delta p_i$ and $\Delta p_j$ are the electricity price changes at time $t_i$ and $t_j$, respectively.

Therefore, the elastic coefficient matrix made of self-elasticity coefficient and mutual-elasticity coefficient within one day can be expressed as,

\[
\Lambda = \begin{bmatrix}
\delta_{11} & \delta_{12} & B & \delta_{1T} \\
\delta_{21} & \delta_{22} & B & \delta_{2T} \\
C & C & C & C \\
\delta_{T1} & \delta_{T1} & B & \delta_{TT}
\end{bmatrix}
\] (3)

Where $T$ is the number of period.

When the elastic coefficient matrix is obtained, the load of each period after the TOU is adopted can be calculated as follows,

\[
\begin{bmatrix}
L_{1}(1) \\
L_{2}(2) \\
C \\
L_{T}(T)
\end{bmatrix} = \begin{bmatrix}
L_{n}(1) \\
L_{n}(2) \\
C \\
L_{n}(T)
\end{bmatrix} + \begin{bmatrix}
0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 \\
C & C & C & C \\
0 & 0 & 0 & L_{n}(1)
\end{bmatrix} \Lambda \begin{bmatrix}
\Delta p_{1}(1) \\
\Delta p_{2}(2) \\
C \\
\Delta p_{T}(T)
\end{bmatrix}
\] (4)

2.2 Predictive Model of DG

In order to reduce the error of the probability model to predict the DG output, we put forward a method of PSO-BP Algorithm to predict the output of DG. It is found that, among many WGs prediction methods, the PSO-BP neural network algorithm not only has a higher prediction accuracy but also reduce calculation time. So, the PSO-BP neural network algorithm is selected in this paper [14].

Firstly, the parameters of BP neural network and the initial velocity and position of PSO are initialized.

\[
\begin{align*}
U_{ij} & = U_{ij} + \lambda X_j (1 - X_j) P_i \sum_{k=1}^{m} U_{ik} e_k \\
U_{jk} & = U_{jk} + \lambda S_i
\end{align*}
\] (5)
Where \( p \) and \( s \) are the input of input layer and the output of hidden layer, respectively; \( \lambda \) is the learning factor; \( e \) is the minimum error; \( U \) is the connection weight of input layer and hidden layer; \( V \) is the weight of hidden layer and output layer.

\[
\begin{align*}
  a_j &= a_j + \lambda X_j (1 - X_j) \sum_{k=1}^{n} U_{jk} e_k \\
  b_k &= b_k + \lambda e_k 
\end{align*}
\]  

(6)

Where \( a \) and \( b \) are the threshold of hidden layer and output layer, respectively.

Then, the historical data of various types of DG are used as input layer for training, and calculate the fitness of each particle

\[
f = \min \sqrt{\frac{\sum_{j=1}^{n} (P_j - Q_j)^2}{n}}
\]  

(7)

Where \( P \) and \( Q \) are the target output and actual output of the training model, respectively. \( n \) is the number of training samples.

After that, PSO is used to optimize the individual optimal value and the global optimal value. The velocity and position of each particle in the PSO are updated as follows,

\[
\begin{align*}
  v^t_i &= \phi^1 v^t_i + \phi^2 (P_{\text{best}}^t - x^t_i) + \phi^3 (G_{\text{best}}^t - x^t_i) \\
  x^t_i &= x^t_i + v^t_i 
\end{align*}
\]  

(8)

Where \( \phi^1 \) and \( \phi^2 \) are the cognitive factors and social factors, respectively; \( \phi^3 \) is the random number distributed between \([0,1]\); \( P_{\text{best}}^t \) is the individual optimal extremum; and \( G_{\text{best}}^t \) is the global optimal.

When the termination condition is satisfied, the search is stopped and the optimal prediction curve of the DG is output.

3. Model of V2G Scheduling

3.1. Multi-objective Function

In order to guarantee the stable operation of distribution network and the economic benefit of users, a multi-objective V2G scheduling model is proposed in this paper. We establish two objective functions including load peak-valley difference and user charging and discharging revenue.

3.1.1. Minimum load peak-valley difference

\[
\min f_i = [\max(P_{\text{load}}(t) + P_{\text{ev}}(t)) - \min(P_{\text{load}}(t) + P_{\text{ev}}(t))]
\]  

(9)

\[
P_{\text{ev}}(t) = \sum_{i=1}^{I} P_{\text{ev},ci}(t) + \sum_{j=1}^{J} P_{\text{ev},cj}(t)
\]  

(10)
Where $P_{\text{load}}(t)$ and $P_e(t)$ are the distribution network load and EV load at time $t$, respectively; $P_{\text{dev}}(t)$ is the $i$th power of EV; $P_{\text{ev.d}}(t)$ is the $i$th power of EV; $I$ and $J$ are the number of charging EV and discharging EV, respectively.

3.1.2. Maximum user charging and discharging revenue

$$\max f_2 = \sum_{t \in \Omega} P_d(t)P_{\text{ev.d}}(t) - \sum_{t \in \Omega} P_e(t)P_{\text{ev.c}}(t)$$

Where $P_d(t)$ and $P_e(t)$ are the discharging electricity prices of EV at time $t$; $P_{\text{d.c}}(t)$ and $P_{\text{c.d}}(t)$ are the discharging power of EV at time $t$; $P_{\text{d.c}}(t)$ and $P_{\text{c.d}}(t)$ are the charging power of EV at time $t$; $\Omega$ is the set of time periods. In addition, $t \neq t'$.

3.2. Constraints

3.2.1. Power balance constraint

$$\begin{cases}
P_{\text{load}}(t) + P_{\text{DG}}(t) = P_{\text{dev}}(t) + P_{e}(t) + P_{\text{anc}}(t) \\
P_{\text{load}}(t) + Q_{\text{DG}}(t) = Q_{\text{dev}}(t) + Q_{e}(t) + Q_{\text{anc}}(t)
\end{cases}$$

Where $P_{\text{dev}}(t)$ and $P_{\text{DG}}(t)$ are the active power input by the superior power grid and DG at time $t$, respectively; $P_{\text{anc}}(t)$ is the active power loss of line at time $t$; $Q_{\text{dev}}(t)$ and $Q_{\text{DG}}(t)$ are the reactive power input by the superior power grid and DG at time $t$, respectively; $Q_{\text{anc}}(t)$ and $Q_e(t)$ are the reactive power of load and EV at time $t$ respectively; $Q_{\text{anc}}(t)$ is the reactive power loss of line at time $t$.

3.2.2. Constraint of voltage and current

$$\begin{cases}
V_{\text{min}} \leq V \leq V_{\text{max}} \\
I_{\text{min}} \leq I \leq I_{\text{max}}
\end{cases}$$

Where $V_{\text{min}}$ and $V_{\text{max}}$ are the lower and upper of voltage, respectively; $I_{\text{min}}$ and $I_{\text{max}}$ are the lower and upper of current, respectively.

3.2.3. Constraint of DG output

$$\begin{cases}
P_{\text{DG}}^{\text{min}} \leq P_{\text{DG}} \leq P_{\text{DG}}^{\text{max}} \\
Q_{\text{DG}}^{\text{min}} \leq Q_{\text{DG}} \leq Q_{\text{DG}}^{\text{max}}
\end{cases}$$

Where $P_{\text{DG}}^{\text{min}}$ and $P_{\text{DG}}^{\text{max}}$ are the lower and upper of active power of DG, respectively; $Q_{\text{DG}}^{\text{min}}$ and $Q_{\text{DG}}^{\text{max}}$ are the lower and upper of reactive power of DG, respectively.

4) Constraint of V2G
\[
\begin{align*}
    x_{c,i} + x_{d,i} & \leq 1 \\
    P_{c,\min} & \leq P_c \leq P_{c,\max} \\
    P_{d,\min} & \leq P_d \leq P_{d,\max} \\
    SOC_{\min} & \leq SOC \leq SOC_{\max}
\end{align*}
\] (15)

Where \(x_{c,i}\) and \(x_{d,i}\) are the binary variables of the charging and discharging state of the \(i^{th}\) EV, respectively; \(P_{c,\min}\) and \(P_{c,\max}\) are the lower and upper of charging power of EV, respectively; \(P_{d,\min}\) and \(P_{d,\max}\) are the lower and upper of discharging power of EV, respectively; \(SOC_{\min}\) and \(SOC_{\max}\) are the lower and upper of state of charge of battery of EV, respectively.

3.3. Solving the Model

Although the particle swarm optimization (PSO) shows a good optimization ability when solving the optimization function, and can find approximate solution quickly by iterative optimization, the PSO is easy to fall into local optimization, resulting in large error [15].

In order to overcome the shortcomings of PSO, this paper proposes an IPSO, which avoids local optimization by improving the weight of PSO. In the IPSO, the weight is given by

\[
\omega = \begin{cases} 
    \omega_{\min} - \frac{(\omega_{\max} - \omega_{\min}) \times (f - f_{\min})}{f_{\max} - f_{\min}}, & f \leq f_{\min} \\
    \omega_{\max}, & f > f_{\max} 
\end{cases}
\] (16)

Where \(\omega_{\min}\) and \(\omega_{\max}\) are the lower and upper of the weight, respectively; \(f\) is the fitness function value; \(f_{\min}\) is the minimum fitness function value; \(f_{\max}\) is the average of all fitness function value.

4. Simulation Analysis

4.1. System Parameter Setting

A modified IEEE-33 node test distribution system is applied to evaluate the effectiveness of the optimal V2G method considering uncertainty of distributed generation and load, as shown in fig.1. There are two kind of DG installed in the test distribution system. One wind generation is installed in Node 17. Two solar photovoltaic generations are allocated in Node 10, 24. The residential EVs cover the nodes of 9 to 18, and 29 to 33. In addition, we assumed that there are 1000EVs involved in V2G service in the distribution network. The load data with peak load is 3.084+2.547MVA. The base line values of line voltage and three-phase power are 12.66kV and 10MVA, respectively.

![Fig.1 The modified IEEE-33 node test distribution network](image-url)

4.2. The Results of V2G Scheduling

In order to verify the scheduling effect of the proposed method, the following cases are considered:
Case 1 considers the V2G scheduling, and does not deal with the uncertainty of DG and load demand.

Case 2 considers the V2G scheduling, uses PSO-BP to predict the output power of the DG, and does not consider the uncertainty of load demand.

Case 3 considers the V2G scheduling, uses TOU to reduce the uncertainty of the load demand, and does not consider the uncertainty of DG.

Case 4 considers the V2G scheduling, uses the method proposed in this paper.

As shown in Fig.2, when V2G scheduling is performed without considering the uncertainty of load and DG in the distribution network, the load curve will still have a large peak-valley difference. This is because the uncertainty of the load and DG will cause great trouble to the user’s behavior choice and reduce the scheduling effect of V2G. But when we start to consider the impact of uncertainty, we can see that case 2, 3, 4 can reduce the peak-valley difference of load. As case 4 has the best effect because it considers the uncertainty in two aspects (DG and load).

Table 1 presents the results of the comparison of load peak-valley difference and user revenue in different cases. From the table, we can see that compared with case1, the peak valley difference of case 2, 3 and 4 is reduced by 22.2%, 35.8%, 42.8%, respectively. The reason we have analyzed in the previous paragraph. In addition, we can also find that with the more uncertain factors considered, the better the economic benefits of users through V2G scheduling. This is because when the uncertainty of load and DG is considered in V2G scheduling, the charging/discharging behaviors of users will be more guaranteed and will not change due to the disturbance of uncertain factors.

| Case 1 | Case 2 | Case 3 | Case 4 |
|--------|--------|--------|--------|
| Peak-valley difference (MW) | 0.1692 | 0.1316 | 0.1087 | 0.0968 |
| User’s revenue ($) | 4.12 | 6.37 | 6.91 | 9.58 |

Fig.2 Optimal results of different cases

Finally, comparison of the voltage fluctuation of the four cases is shown in Fig.3. From Fig.3, we can see case 2, 3, 4 can reduce the voltage fluctuation and ensure the stability of the distribution network. And case 4 performs best, which also shows that in V2G scheduling, the more uncertainty can be reduced, the better the V2G scheduling effect.
5. Conclusion
In order to reduce the negative impact of load and DG uncertainty on V2G scheduling, this paper proposes an optimal V2G method. The TOU and PSO-BP is used to reduce the uncertainty of load demand predict the output of DG, respectively. Finally, an IPSO is adopted to calculate the proposed model. In the simulation, we prove the effectiveness of the proposed method by comparing four different cases. Whether it is to reduce the load peak-to-valley difference, or to increase the user's economic benefits and ensure the stability of the distribution network, the method proposed in this paper has a better performance.

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![Fig. 3 Comparison of voltage fluctuation in different cases](image-url)
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