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Charging and Discharging Control Strategy of Electric Vehicle Grid Connected Under Clean Energy

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Abstract.

A control strategy for electric vehicle charging station under clean energy is proposed in this paper. Its core is to determine the operation mode of the charging station according to the maximum power output of the photovoltaic system and the state of charge of the energy storage battery. The system can realise the coordinated operation of photovoltaic power generation, energy storage system charging and discharging, charging station demand and grid connection. The bidirectional DC/DC converter at the energy storage end adopts voltage and current double closed loop control. In order to avoid frequent charging and discharging of storage battery, bus voltage layered control method is adopted. The experimental results show that the adopted control strategy can enable the electric vehicle charging station to switch effectively between various operation modes, which verify the effectiveness of the system control strategy.

Keywords: clean energy, electric vehicle, control strategy, bidirectional DC/DC converter.

AIMS AND BACKGROUND

In the micro grid, photovoltaic power generation has become the first choice to provide electric energy for electric vehicles due to its advantages of renewable, clean, pollution-free and easy access to light energy[1]. In terms of improving the power supply reliability of the power system and reducing energy consumption, the application of organic combination of electric vehicles and photovoltaic power generation systems has great potential[2-4]. Therefore, based on the grid connected micro grid, research the synergy between the charging and discharging of electric vehicles and photovoltaic power generation, control the charging and discharging process of electric vehicles by using reasonable strategies, achieve the purpose of improving the utilisation of photovoltaic, and reduce the network loss of active power in the micro grid[5,6]. Taking the mobile energy storage characteristics of electric vehicles as the starting point, systematically carrying out research on the charging and discharging of electric vehicles in the microgrid will help more comprehensively and effectively use the charging and discharging performance of electric vehicles to achieve the V2G function, achieve the goals of energy conservation and emission reduction, renewable energy consumption and lower energy storage configuration[7].

CHARGING AND DISCHARGING BEHAVIOR CHARACTERISTICS OF ELECTRIC VEHICLES

In the power grid, the whole electric vehicle group can be classified according to the different states, including driving and stopping. If the electric vehicle is running, it will not be connected to the power grid and will not participate in grid interaction. When the vehicle is stopped, the vehicle may not be connected to the power grid because there may not be facilities with V2G function at the parking point, or the residual power of the power battery meets the requirements of the vehicle owner. If the electric vehicle is not connected to the grid, it will not be connected to the grid and will not participate in grid interaction. For electric vehicles connected to the power grid, if they do not participate in the interaction, they will become the load of the power grid, and the remaining parts involved in the interaction will become the energy storage of the power grid[8].

In the process of studying the charging and discharging demand model of electric vehicles, it is the basis of the research to reasonably predict the ownership of electric vehicles. In recent years, due to the increasingly mature battery technology and charging technology and the strong support and encouragement of the government, the electric vehicle industry has developed rapidly, and its ownership has also made a breakthrough. If the bottleneck of driving range and charging mode is completely broken through in technology, the number of electric vehicles will grow explosively. The number of new energy vehicles in China has grown by leaps and bounds from 20 400 in 2012 to 1 729 000 in 2017 (Refs 9 and 10). Among them, the number of new energy vehicles increased rapidly in 2013 and 2015, and then tended to grow steadily. In the future, new energy vehicles will grow steadily in the context of the government subsidy policy and the relay of the double credit policy. It can be expected that electric vehicles will be popularized in daily life in the future. At present, electric vehicles are in the early stage of rapid development, and their ownership will increase exponentially.

The daily driving mileage is determined by the driving habits and driving characteristics of the car owners, which can directly determine the capacity of electric vehicles to participate in V2G interaction, and indirectly reflect the electric energy consumed by electric vehicles in a day. According to the analysis of the survey data of the U.S. Department of Transportation on household vehicles in 2001, about 14% of the household vehicles are not used in a day, 43.5% of the vehicles have a daily mileage of less than 32 km, and 83.7% of the vehicles have a daily mileage of less than 97 km.

First the probability distribution of daily mileage d of electric vehicle owners is obtained by maximum likelihood estimation . It can be seen that the probability distribution is approximately subject to the lognormal distribution, and the probability density function expression is shown in the following equation:

$$f_D(d) = \frac{1}{d\sigma_D\sqrt{2\pi}} exp\left[-\frac{(Ind-\mu_D)^2}{2\sigma_D^2}\right] \quad (1)$$

where d is the daily mileage, the value range is $0 < d \leq 180$, and the unit is km; μ_D and σ_D is a distribution parameter, which is the expected value of daily mileage and its corresponding standard deviation. It can be calculated according to the statistical mean value mn and standard deviation sd of EVs daily mileage, as shown:

$$\begin{cases} \mu_D = In(mn) - 0.5 \times In(1 + sd^2/mn^2) \\ \sigma_D = \sqrt{In(1 + sd^2/mn^2)} \end{cases} \quad (2)$$

In this paper, the travel habits of electric private cars on normal working days are taken as the research object. Assuming that the car owners are connected to the power grid at the last moment when they stop driving, the probability distribution of the initial charging and discharging time rule of electric vehicles can be obtained. The research shows that the probability distribution of the initial charging and discharging time of the vehicle owner is approximately subject to the normal distribution, as shown in the following equation:

$$f_s(x) \begin{cases} \frac{1}{\sigma_s\sqrt{2\pi}} exp\left[-\frac{(x-\mu_s)^2}{2\sigma_s^2}\right], (\mu_s - 12) < x \leq 24 \\ \frac{1}{\sigma_s\sqrt{2\pi}} exp\left[-\frac{(x+24-\mu_s)^2}{2\sigma_s^2}\right], 0 < x \leq (\mu_s - 12) \end{cases} \quad (3)$$

The length of time that an electric vehicle experiences from stopping at a certain place to leaving the place is its stay time, while the charging time refers to the length of time that the battery experiences from initial state of charge to full charge (SOC=1). The relationship between charging time and dwell time is as follows:

$$T_c = \begin{cases} T_{stay}, T_{stay} < T_{need} \\ T_{need}, T_{stay} \geq T_{need} \end{cases} \quad (4)$$

$$T_{stay} = T_{leave} - T_{enter} \quad (5)$$

$$T_{need} = T_{01} * (1 - SOC_0) \quad (6)$$

where T_c is the vehicle charging time; T_{need} - the vehicle charging demand; T_{stay} - the length of vehicle stay; T_{enter} - the time of vehicle entry; T_{leave} - the time when the vehicle leaves; T_{01} - the time taken for the electric vehicle power battery from SOC=0 to SOC=1.

The state of charge of each electric vehicle is:

$$S_{i,t} = \begin{cases} 1, T_{enter} < t \leq (T_{enter} + T_c) \\ 0, t \leq T_{enter}, t > (T_{enter} + T_c) \end{cases} \quad (7)$$

where $S_{i,t}$ is the charging state of vehicle i at time t, taking 1 as charging, taking 0 as not charging; t = 1, 2,..., 24 (**s**). Suppose that there are N electric vehicles that need to be charged in one day, i = 1,2,..., N. The total demand for charging at each time of the day can be obtained by adding the charging power of a single electric vehicle:

$$P_{ev,t} = \sum_{i=1}^{N} P_{ci} * S_{i,t} \quad (8)$$

where $P_{ev.t}$ is the total demand for charging N electric vehicles at time t; P_{ci} - the charging power of vehicle i.

Assuming that the electric vehicle charging power is a fixed value and P_c, the formula for calculating the charging duration T_c

is:

$$T_c = \frac{(SOC_{\max} - SOC_{\min}) \times C_b}{P_c} \quad (9)$$

RESEARCH ALGORITHM AND ITS SOLUTION

PSO is a population-based optimisation algorithm. It is inspired by the collective behaviour of birds in hunting, simulates and studies the behavior of birds in hunting, and finds that birds seek food in a cooperative way, and members of the group constantly change the direction of searching for food by obtaining experience from themselves or from other members. PSO algorithm has the advantages of simplicity, easy implementation, few parameter settings, and does not need gradient information in the process of optimisation.

The PSO algorithm takes the general random solution as the starting point, and uses the iterative optimisation method to find the global optimal solution by tracking the current local optimal value. PSO algorithm and genetic algorithm are evolutionary algorithms based on global random search. Genetic algorithm has more parameter settings than PSO algorithm through coding, cross mutation and other links. At the same time, compared with PSO algorithm, the programming of genetic algorithm is more complex. After the corresponding optimal solution is obtained through coding, decoding steps are also required. Moreover, parameter setting is more complex, program debugging is more difficult, and convergence is relatively slow. PSO algorithm obtains the optimal solution in the process by updating the information such as particle velocity and position. Although the PSO algorithm has the defect of premature convergence, its principle is relatively simple, the parameter settings in the debugging process are relatively few, and there is no significant difference in the effect performance between genetic algorithm and PSO algorithm in solving optimisation problems, so this paper selects the improved particle swarm optimisation algorithm.

Due to the loss of diversity of the population, the probability of the standard PSO algorithm reaching the local optimum is increased, which leads to premature convergence of the algorithm when solving complex problems, and ultimately the optimal solution sought is not the global optimal solution. In view of the defects and deficiencies of the standard PSO algorithm, and in order to enhance the global search and optimisation capabilities of the standard PSO algorithm and the adaptability to different optimisation problems, a mutual learning particle swarm optimisation algorithm is proposed based on the standard PSO algorithm. This algorithm introduces the constructive team concept in human society (that is, the behavior of different groups learning from each other) into the standard PSO algorithm, and forms an improved particle swarm optimisation with inter warm interactive learning strategy (IIL-PSO) based on the mutual learning strategy between populations to overcome the loss of diversity of typical particle swarm learning strategies.

In order to verify the effectiveness and superiority of IIL-PSO algorithm, four classical objective functions are selected for optimisation testing. It is known that in the definition domain, the Schaffer function only has 1 global minimum value 0, which is located at the point (0,0). The Multimodal function has four global maximums 2.118, which are symmetrically distributed in (+0.64,+0.64), (+0.64, -0.64), (-0.64,+0.64), (-0.64, -0.64), and (- 0.64). In the middle region of the definition domain, there are local limit values that are very close to the global maximum; the Griewank function only has 1 global minimum value 0, which is located at the point (0,0); the Shubert function is a multimodal function. There are 760 local minima in its definition domain, and there are 18 points in the global minimum of the function - 186.731.

The Schaffer function expression is shown in the following equation:

$$f_1 = f(x_1, x_2) = 0.5 + \frac{\left(\sin\sqrt{x_1^2 + x_2^2}\right)^2 - 0.5}{\left(1 + 0.001\left(x_1^2 + x_2^2\right)\right)^2} \quad (10)$$

Multimodal function expression is shown in equation (11):

$$f_2 = f(x, y) = -\left(1 + x \square \sin(4\pi x) - y \square \sin(4\pi y + x + 1) + \frac{\sin\left(6\sqrt{x^2 + y^2}\right)}{6\sqrt{x^2 + y^2} + 10^{-15}}\right) \quad (11)$$

The Griewank function expression is shown as follows:

$$f_3 = f(x_i) = \sum_{i=1}^{N} \frac{x_i^2}{4000} - \overset{i=1}{\overset{N}{\prod}} \cos\left(\frac{x_i}{\sqrt{i}}\right) + 1 \quad (12)$$

The Shubert function expression is shown in equation (13):

$$f_4 = f(x,y) = \{\sum_{i=1}^{5} i\cos[(i+1)x+1]\} \times \{\sum_{i=1}^{5} i\cos[(i+1)y+1]\} \quad (13)$$

Through the simulation comparison of the two algorithms, the comparison results between IIL-PS4 algorithm and standard PSO algorithm are analyzed. The former has better optimisation performance and more accurate search, which verifies the superiority of IIL-PSO algorithm.

RESULTS AND DISCUSSION

The idle electric vehicle is connected to and integrated into the microgrid through an intelligent charging device and its charging or discharging is controlled by the micro grid. When the electric vehicle is connected to the micro grid, the charging and discharging of the electric vehicle can be controlled to achieve energy storage under the premise of meeting the daily driving needs of the vehicle owner and obtaining their consent. For a long time, reducing the peak valley difference of the equivalent load and the network loss of the active power in the power grid has been the focus of the power system.

In this paper, through orderly management of charging and discharging power of electric vehicles, the problem of increasing load peak valley difference caused by its access can be alleviated to a certain extent. Taking electric private car as the research object, considering its V2G interaction in conventional charging and discharging mode, an optimisation model with electric vehicle charging and discharging power as the variable is established. In this paper, a day is divided into 24 time periods. The charging and discharging power of each vehicle in each time period is used as the variable for control, and the mean square difference of the load curve is minimized as the objective function.

$$\min f_1 = \sqrt{\frac{\sum_{1\in T}[P_s(t)-P_{av}(t)]^2}{N_k-1}} \quad (14)$$

$$P_{av} = \frac{1}{T}\sum_{t=1}^{T} P_s(t) \quad (15)$$

$$P_s(t) P(t) + P_{ev}(t) + P_{pv}(t) + P_{bat}(t) \quad (16)$$

where T is the duration of a day; N_k - the total number of sampling points in a day, that is, 24; $P_s(t)$ - the equivalent load power of microgrid in t period; P_{av} - the average load power of the microgrid; $P(t)$ - the load power of microgrid in t period; $P_{ev}(t)$ - the electric vehicle charging and discharging power of the microgrid in t period; P_{pv} (t) - the output power of photovoltaic power generation in t period, and P_{bat} (t) - the charging and discharging power of storage battery in t period.

Through the power flow calculation in the microgrid, the charging and discharging optimisation scheme of electric vehicles at different nodes is determined with the goal of minimising the network loss of active power in the microgrid within a day. The objective function expression is shown in equation (17):

$$\min f_2 = \sum_{j=1}^{24}\left[\sum_{(a,b)\in S_L} G_{ab}\left(U_{a,j}^2 + U_{b,j}^2 - 2U_{a,j}U_{b,j}\cos\varphi_{ab,j}\right)\right]\Delta t \quad (17)$$

In this paper, from the perspective of fully utilising renewable distributed power generation to charge electric vehicles, the optimisation model of orderly charging and discharging of electric vehicles is established under the background of grid connected operation of micro grid. IIL-PSO algorithm is used to solve the problem, MATLAB language is used to write the program, and the simulation is completed on Dell (3.60GHz, 4.00GB)/PC computer to verify the accuracy and effectiveness of the models and methods built.

Take the microgrid system as shown in Fig. 1 for example analysis, among which 6 nodes are uniformly distributed, and electric vehicle charging piles are set as V2G access points. It can be seen from Fig. 1 that the microgrid contains charge pile CP, conventional load L, battery pack BAT and PV of photovoltaic power station. The voltage level of the microgrid is 0.4kV, which is on the low-voltage distribution network side. The microgrid is connected to the power distribution network through the public emergency junction point for energy exchange. When the static switch is turned on, the microgrid operates in an isolated island. The energy flows only within the micro grid, and is mainly supplied by photovoltaic power generation for electric vehicles. When the number of electric vehicles to be charged is small, the surplus photovoltaic output can only be discarded to reduce the utilization rate of photovoltaic.

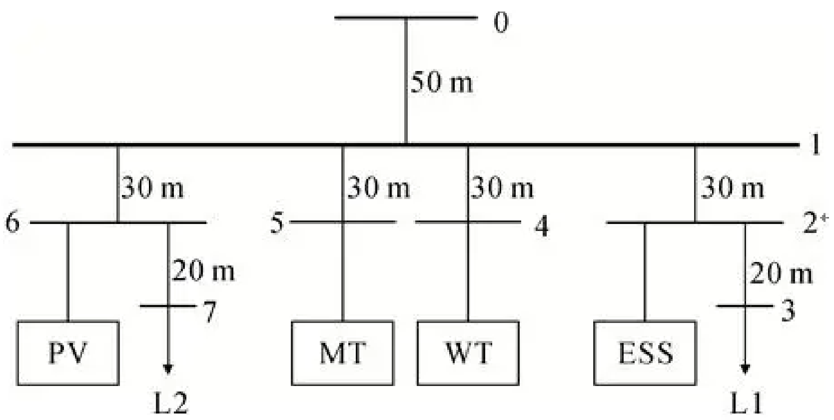

Fig. 1. Microgrid structure diagram

The static switch is closed, and the microgrid works in the grid connected operation mode. PV power generation is connected to AC bus through DC/AC inverter, and the inverter adopts maximum power point tracking control strategy. The energy storage system is connected to the AC bus through the bidirectional DC/AC converter to regulate the energy and power of the microgrid. The photovoltaic output power in the microgrid gives priority to providing electric energy for the electric vehicle power battery, followed by the battery pack. In addition, if there is surplus photovoltaic output, the surplus power will be transmitted from the microgrid to the distribution network to provide power for the load of the distribution network; When the photovoltaic output is insufficient, the electric vehicle releases electric energy first, followed by the battery pack. If the discharge of both batteries still can not meet the load demand, the electric energy will be obtained from the distribution network. Generally, the static switch is kept closed, and the microgrid operates in grid connection mode.

CONCLUSIONS

Microgrid is a kind of microgrid system which is generated to solve the contradiction between renewable distributed generation and power grid. It has the advantages of flexibility, economy, environmental protection, etc. It is the trend of future power system development. The electric vehicle can be connected to the microgrid as load or energy storage, which not only alleviates the adverse effects caused by intermittent photovoltaic output, but also can use photovoltaic power generation to provide electric energy for electric vehicles, which is conducive to reducing indirect carbon emissions.

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