ATLANTIS PRESS

Advances in Intelligent Systems Research (AISR), volume 145

2017 International Conference on Electronic Industry and Automation (EIA 2017)

Research on Coordinated Scheduling of Electric Vehicle Charging/Discharging and Renewable Energy Power Generation

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***Abstract*—With the dramatic increase of plug-in electric vehicles (EVs) grid penetration, the random characteristics of EVs will influence the normal operation of the power system. Given this background, a multi-objective optimization model is proposed in this paper to mitigate the peak-to-valley deference of equivalent load and reduce the active power losses of the distributed grid for a regional electrical power system, taking the storage capacity of EVs, the charging/discharging power, the distributed power flow, and the driving characteristics of EVs into consideration. Defining each objective membership function, multi-objective optimization problem is reformulated into a nonlinear single-objective programming problem by means of fuzzy satisfaction-maximizing method, and this nonlinear single-objective programming problem is solved by using modified particle swarm optimization algorithm based on hybrid mechanism. Simulation results indicate that the proposed model and algorithm can flat the curve of equivalent load, reduce the reserved capacity in adjusting the peak, optimize the active power losses and provide the voltage support for the system.**

Keywords-component; electric vehicle; fuzzy optimization; PSO; active power losses; peak-to-valley deference ratio

I. INTRODUCTION

Photovoltaic (PV) has obtained a wide range of applications with the development of renewable energy techniques. The penetration of PV is also increased in China with about 17.8 GW being installed in 2015, the greatest installation capacity in the world. Because of intermittent and limited predictable nature, PV raises a challenge in maintaining a safe and economic power grid [1]. Electric vehicles (EVs) have been becoming attractive for green transportation to cope with global energy crisis and environmental pollution. Previous statistics have shown that China has 120,000 EVs by 2014, with the growth rate of more than 70% every year. It is expected that the occupancy rate of EVs in China will amount to about 25% of the global market by 2020. The out-of-order charging of large-scale EVs will have a negative influence on the system losses, the operation costs, and the harmonic pollution to a safe and economic operation of the power grid. According to the survey in [2], a vast majority of EVs are stopped in 96% of the time each day. By using the V2G technique [3], EVs are the loads of the power system in a state of charging, and are emergent power sources when discharging [4].

In recent years, integrating renewable energy generation with EVs' charging and discharging has been becoming a research focus all over the world. In[5],in consideration of the wind power output distribution of the Jiuquan wind farm, a collaborative dispatching model with the objective to minimize the running costs of micro-grid system was developed. The feasibility and efficiency of accommodating wind power was validated through IEEE 9 node distribution system. By minimizing the output fluctuation of renewable generation and maximizing the income of EV users, a multi-objective optimization model was built in [6]. In this model, the grid-connectable EVs, the wind power generation systems, and the photovoltaic generation systems are simultaneously taken into account. According to the energy management of micro-grids with both EVs and the PV-energy storage, an energy management model was developed in [7] to reduce the operation costs, maintain the load balance, and enhance the service reliability. To analyze the possibility of dispatched EVs' charging to reduce the load fluctuation and increase its capability of accommodating the wind power, a multi-scale synergistic dispatch model was developed in [8]. PV-assisted charging stations for EVs have been becoming a typical integration of consuming renewable resources in [9]. To this end, a variety

of countries have been building a great number of demonstration projects, and the converter and the control techniques related to EVs' charging have been verified. However, as the number of EVs increases, it is of necessity to consider reasonable charging/discharging optimization strategies. On one hand, taking the quantity of electricity stored in a battery, the charging/discharging power and the distributed power flow in an optimization strategy into consideration, mitigating the peak-to-valley ratio of equivalent loads and reducing the reserved capacity in adjusting the peak to making full use of renewable energy outputs are of necessity. On the other hand, according to PV generation and load forecasting, decreasing the active power losses of the distributed grid by controlling EVs' charging/discharging power and improving the economy and the security of the distributed network operation are also required. This issue belongs to a combinatorial optimization problem with constraints, and previous optimization algorithms have not solved it. Due to the simplicity of particle swarm optimization (PSO), PSO has been applied to solve various power system problems [10].

This paper proposes a optimal dispatch model to reduce the peak-to-valley ratio of equivalent loads and the active power losses of the distributed grid. To effectively solve the above model, multi-objective optimization problem is reformulated into a nonlinear single-objective programming problem by means of fuzzy satisfaction-maximizing method. Particle swarm optimization algorithm is adopted to solve this optimization problem. The proposed model and algorithm are applied to the IEEE 33-bus test system, and the simulation results indicate the feasibility and efficiency.

II. THE PROPOSED OPTIMAL DISPATCH MODEL

EVs have such types of taxi, official cars, buses, and private cars. In this paper, only private cars are considered, and they interact with the power grid by optimizing the charging/discharging power since private cars often have long stopping time and enough quantity of electricity stored in a battery.

A. The Postulated Conditions of the Model

The postulated conditions of the model are as follows:

(1)An intelligent charging pile provides charging/ discharging service for EVs that can be adjusted according to requirement.

(2)Only the optimization of the charging/discharging power and time are focused on.

(3) EVs are uniformly distributed among nodes.

(4)The communication between EVs and the distributed network is real-time.

(5)EVs connecting with the grid can be dispatched all the day.

(6)Equivalent loads and the EVs' charging and discharging power remain unchanged at each period.

(7) EVs' daily mileage obeys the lognormal distribution, and time in stopping the last travel obeys the normal distribution [11].

(8)Develop appropriate discharging incentive policies and give appropriate financial aid to discharging vehicles participating in scheduling.

B. The Objective Functions

Mitigating the peak-to-valley ratio of equivalent loads and reducing the active power losses of the distributed grid are of considerable concern of the power system. On the premise of normally operating the system, optimizing the EVs' charging and discharging power is of importance to mitigate the peak-to-valley ratio, reduce the losses of the distributed grid, and improve the economy and the security of the distributed network operation.

The mean square deviation of the loads reflects the fluctuation of these loads, and the smaller the mean square deviation, the smaller the fluctuation. In this paper, the charging and discharging power of EVs aggregation under each node is regarded as the optimized variables. The optimal solution of the optimization problem should minimize the sum of the mean square deviations of equivalent daily loads, i.e.,

$$\min F_1 = \sum_{j=1}^{24} (P_{Lj} - P_{Sj} - P_{av,j} + \sum_{i=1}^{n} P_{ij})^2 \cdot \tag{1}$$

where P_{Lj}, P_{Sj}, $P_{av,j}$, and P_{ij} denote the active load of the system, the PV output, the average equivalent load, and the charging and discharging power of EVs of node i at the j_{th} time period, respectively.

The optimal solution of the optimization problem should minimize the active losses of the distributed system in a day, i.e.,

$$\min F_2 = \sum_{j=1}^{24} [\sum_{(a,b)\in S_L} G_{ab}(U_{a,j}^2 + U_{b,j}^2 - 2U_{a,j}U_{b,j}\cos\varphi_{ab,j})]\Delta t \,. \tag{2}$$

where S_L represents collection of all branches in the system, $U_{a,j}$, $U_{b,j}$ mean the voltage amplitude of the first and last node of each branch at j period, $\varphi_{ab,j} = \varphi_{a,j} - \varphi_{b,j}$ is the difference of voltage phase angle between branch head and terminal node, G_{ab} is real part of mutual admittance, Δt denotes the time interval, $\Delta t = 1h$.

C. The Constraints

1) The capacity of EVs' batteries should satisfy that

$$\Delta C_{i\min} \le \Delta C_{ij} \le \Delta C_{i\max} \,. \tag{3}$$

where $\Delta C_{i\min}$, ΔC_{ij}, and $\Delta C_{i\max}$ denote the minimal capacity of EVs' batteries, the capacity of EVs' batteries at period j, and the maximal capacity of EVs' batteries, respectively.

2) The charging/discharging power should satisfy that

$$P_{i\min} \le P_{ij} \le P_{j\max} \tag{4}$$

where $P_{i\min}$ represents the minimal power of charging and discharging, $P_{i\max}$ means the maximal power of charging and discharging.

3) The node voltage amplitude should satisfy that

$$U_{\min} \le U_a \le U_{\max} \tag{5}$$

where U_a is the voltage of node a, $U_{\min}$ and $U_{\max}$ are the minimal and the maximal voltages of each node, respectively.

4) The node power balance constraint is provided as

$$P_{Ga} + P_{Sa} - P_{La} - P_{EV,a} = U_a \sum_{b=1}^{n} U_b (G_{ab} \cos\delta_{ab} + B_{ab} \sin\delta_{ab}) \tag{6}$$

$$Q_{Ga} + Q_{Sa} - Q_{La} - Q_{EV,a} = U_a \sum_{b=1}^{n} U_b (G_{ab} \sin\delta_{ab} - B_{ab} \cos\delta_{ab}) \tag{7}$$

where P_{Ga} and Q_{Ga} are the injected active and the reactive power from the external power grid, respectively, P_{Sa} and Q_{Sa} denote the active and the reactive power from the PV system, P_{La} and Q_{La} refer to the active and the reactive loads, $P_{EV,a}$ and $Q_{EV,a}$ denote the changing/discharging active and reactive power of EVs, U_a and U_b are the voltages of the first and the last nodes of each branch, G_{ab} and B_{ab} mean the real and the imaginary parts of the admittance of branch $a-b$, and δ_{ab} denotes the power factor angle of branch $a-b$.

D. Fuzzificatuon of objective function

Fuzzy decision-making method is adopted in this paper to meet the needs of decision makers and the multi-objective optimization problem is fuzzy by calculating the membership function of each optimization objective. The satisfaction of the decision maker to the target value will be reflected by the membership grade, and then the multi-objective fuzzy optimization problem is transformed into a single objective nonlinear optimization problem. It can solve the problem that the weight is difficult to be determined and the dimension is inconsistent. Determining the membership function of each objective function is the key to establish the multi-objective fuzzy optimization model.

For the optimization model established in this paper, it is expected that the fluctuation of equivalent load and the system active power loss are as small as possible under the condition of all the constraints. These two objects are no minimum limit but the Maximum. Therefore, the reducing half line shape is chosen as the membership function of two optimization objectives, and graphs Fig.1 and formulas (8, 9) are shown as follows:

$$\mu(f_1(x)) = \begin{cases} 1 & f_1(x) \le \delta_1 \\ \dfrac{\delta_1 + \delta_{01} - f_1(x)}{\delta_{o1}} & \delta_1 < f_1(x) \le \delta_1 + \delta_{o1} \\ 0 & f_1(x) > \delta_1 + \delta_{o1} \end{cases} \tag{8}$$

$$\mu(f_2(x)) = \begin{cases} 1 & f_2(x) \le \delta_2 \\ \dfrac{\delta_2 + \delta_{o2} - f_2(x)}{\delta_{o2}} & \delta_2 < f_2(x) \le \delta_2 + \delta_{o2} \\ 0 & f_2(x) > \delta_2 + \delta_{o2} \end{cases} \tag{9}$$

where $\mu(f_1(x))$ and $\mu(f_2(x))$ are membership functions of the optimization objective function F_1 and F_2, δ_1 and δ_2 are objective function value of F_1 and F_2, δ_{o1} and δ_{o2} are acceptable increasing value of mean square deviation of equivalent loads and active power loss, ϕ is defined as satisfaction degree of membership function $\mu(f_1(x))$ and $\mu(f_2(x))$.

According to biggest and smallest principle of the fuzzy set theory, i.e.,

$$\phi = \min[\mu(f_1(x), \mu(f_2(x))] \tag{10}$$

Then the problem is transformed into a problem of maximizing ϕ with constraints and mathematical formulas

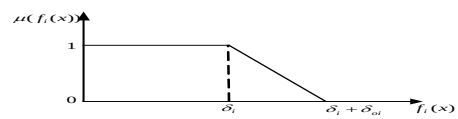

Figure 1. The curve of membership function

are as follows:

$$\max \phi \quad s.t. \begin{cases} \mu(f_1(x)) \ge \phi \\ \mu(f_2(x)) \ge \phi \\ 0 \le \phi \le 1 \\ formula(3-7) \end{cases} \tag{11}$$

The first two terms of the constraint of the type (11) are brought into the feasible region of the formula (8)and(9), and the multi-objective optimization problem can be transformed into a single objective nonlinear programming problem, i.e.,

$$\max \phi \quad s.t. \begin{cases} \delta_{o1}\phi + f_1(x) \le \delta_1 + \delta_{o1} \\ \delta_{o2}\phi + f_2(x) \le \delta_2 + \delta_{o2} \\ 0 \le \phi \le 1 \\ formula(3-7) \end{cases} \tag{12}$$

III. THE OPTIMIZATION ALGORITHM

A. The The Modified Particle Swarm Optimization Algorithm

The study in [12] has shown that PSO is apt to mature convergence when solving high-dimensional optimization problems. To overcome the drawback, a number of particles are selected with the probability of P_c in each iteration and put into a hybrid pool whose size is determined by a parameter, S_p .The offspring particles are generated by randomly blending two parent particles. In this way, offspring particles inherit the advantages of their parents', strength the capability in exploitation, and improve the search results. The position of an offspring particle is updated as follows:

$$\begin{cases} child_1(x) = \rho \cdot pt_1(x) + (1-\rho) \cdot pt_2(x) \\ child_2(x) = (1-\rho) \cdot pt_1(x) + \rho \cdot pt_2(x) \end{cases} \tag{13}$$

where $child(x)$ and $pt(x)$ are the positions of the offspring and the parent particles, respectively.

The speed of an offspring particle is provided as follows:

$$\begin{cases} child_1(v) = \dfrac{pt_1(v) + pt_2(v)}{|pt_1(v) + pt_2(v)|} |pt_1(x)| \\ child_2(v) = \dfrac{pt_1(v) + pt_2(v)}{|pt_1(v) + pt_2(v)|} |pt_2(x)| \end{cases} \tag{14}$$

where $child(v)$ and $pt(v)$ represent the speed of the offspring and the parent particles, respectively.

B. Algorithm Process

In this paper, the charging and discharging power of each vehicle aggregate in each period is taken as the decision variable, and the decision variable is $[P_{11}, P_{12}, \cdots, P_{124}, \cdots, P_{n1}, P_{n2}, \cdots, P_{n24}]$ .The improved particle swarm optimization (PSO) algorithm is adopted to solve the model. The process of tackling the optimization problem considered in this paper is provided as follows:

Step1: Set the values of parameters used in the proposed algorithm. An improved particle swarm optimization (PSO) algorithm is used to get the best optimal solution δ_1 and corresponding active power loss $\delta_2^{''}$ of objective function F_1.

Step2: Set the values of system parameters, and get the best optimal solution δ_2 of corresponding mean square deviation of equivalent load $\delta_1^{''}$ of objective function F_2

Step3:Confirm δ_{o1} and δ_{o2} with $0 < \delta_{o1} < (\delta_1^{''} - \delta_1)$ and $0 < \delta_{o2} < (\delta_2^{''} - \delta_2)$. Under different situations of system requirement, δ_{o1} and δ_{o2} can be telescopic in different degrees, and its value is as small as possible. But it will increase the difficulty of calculation.

Step4:Get the expression of membership function by bringing δ_1 δ_2 δ_{o1} δ_{o2} into formula (9, 10).

Step5:The multi-objective optimization problem is transformed into a single objective problem with the method of maximum and minimum satisfaction.

Step6: The modified PSO algorithm is applied to obtain the active power loss and mean square deviation of equivalent load.

IV. A CASE STUDY

The IEEE 33-bus benchmark system is employed to verify the proposed model and algorithm, whose initial topology is depicted in Fig2. Node 1 is connected with the infinite power grid, and regarded as the slack bus because its voltage amplitude is constant, and the PU value of its voltage amplitude is 1.05. The values of the other parameters are set as follows. The voltage reference value UB=12.66kV, and the power reference value SB=10MVA. For the peak load, the total active load is 3715kW, and the total reactive load is 2300kvar.

The typical load data of this case come from [13], shown as Fig.3.

A. The Parameter Settings

1) The parameter settings and the assumptions of EVs

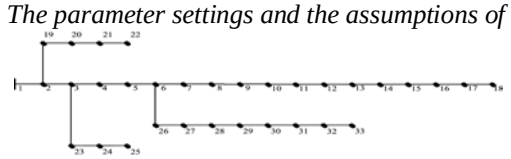

Figure 2. IEEE 33-bus benchmark system

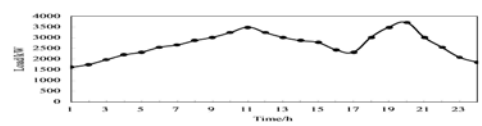

Figure 3. The typical load curve of this case

In [14], this region has 929 subscribers and approximate 4000 residents. In this paper, the number of EVs is assumed to be 200. The number of EVs under each node of the distributed network is equal. The EVs in running are Nissan Altra in this system. According to industry standards [15], the nominal capacity of a battery is 32.78 kW·h, and the charging/discharging power is 6.5 kW. In addition, the energy consumption per kilometer is 0.142 kWh/km, and the power factor of an intelligent charging and discharging machine is 0.95.The penetration of EVs refers to the ratio of the number of scheduling EVs to the total number.

2) The parameter settings and the assumptions of PV generation systems

The PV array area of switching in each node is 150m2, and the photoelectric conversion efficiency is 15%. In this paper, the reactive output of a PV system accounts for 10% of the active output. The average values of intensity parameters at each time period are shown in Table I.

3) The parameter settings and the assumptions of the proposed PSO algorithm

To balance the capabilities between the global and the local search of a PSO algorithm, the inertia weight coefficient is nonlinear and dynamic, shown as follows:

$$\omega = \begin{cases} \omega_{\min} + \dfrac{(\omega_{\max} - \omega_{\min})(f - f_{\min})}{f_{avg} - f_{\min}}, & f \le f_{avg} \\ \omega_{\max} & , f > f_{avg} \end{cases} \tag{15}$$

where $\omega_{\max}$ and $\omega_{\min}$ are the maximal and the minimal coefficients respectively, f denotes the fitness of a particle, f_{avg} and $f_{\min}$ refer to the average and the minimal fitness of all the particles, respectively9.

To make a particle have a larger self- learning ability and a smaller social learning ability in the initial optimization stage, and a smaller self - learning ability and a larger social learning ability in the later period, the following asynchronously changing learning factors are adopted.

TABLE I. THE AVERAGE VALUES OF INTENSITY PARAMETERS AT EACH TIME PERIOD

time	parameters(W/m^2)	time	parameters(W/m^2)
07:00	30	14:00	790
08:00	150	15:00	740
09:00	410	16:00	580
10:00	530	17:00	460
11:00	680	18:00	120
12:00	860	19:00	20
13:00	890		

$$\begin{cases} c1 = c1_0 + \dfrac{c1_1 - c1_0}{t_{\max}} t \\ c2 = c2_0 + \dfrac{c2_1 - c2_0}{t_{\max}} t \end{cases} \tag{16}$$

where $c1_0$ and $c2_0$ are the initial values of $c1$ and $c2$, respectively, $c1_1$ and $c2_1$ mean the final values of $c1$ and $c2$ respectively, $t_{\max}$ denotes the largest number of iterations, and t is the number of iterations.

The swarm size is set to 40, and the value of ρ is randomly chosen in the range of [0, 1]. The range of a particle's velocity is [-1, 1], and the other parameters are set to $P_c = 0.9$, $S_p = 0.2$, $\omega_{\max} = 0.8$, $\omega_{\min} = 0.4$, $F_{1\max} = 6.2856$, and $F_{2\max} = 2.449kW \cdot h$. In addition, the values of the learning factors are chosen as follows: $c1_0 = 2.5$, $c2_0 = 0.5$, $c1_1 = 0.5$, $c2_1 = 2.5$.

B. The Simulation Results

The curves of the equivalent loads with 50% and 100% penetration are given in Fig.4.

Fig.4 demonstrates that the load fluctuation is large, and the random charging load of EVs is increased, deteriorating the load curve of the system. Under the condition of the optimization, EVs charge from the power grid at the period of the valley loads, and discharge to the power grid at the period of the perk loads so as to effectively reduce the peak-to-valley ratio. As the penetration of EVs increases, the effect of EVs to mitigate the peak-to-valley ratio of equivalent loads will be obvious, reducing the reserved capacity in adjusting the peak and enhancing the economy and the stability of the system.

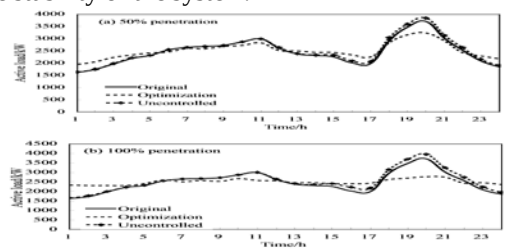

Figure 4. The curves of the equivalent loads with 50% and 100% penetration

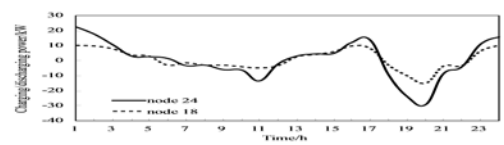

Figure 5. The optimized charging and discharging power curve of a typical node with 100% penetration

The optimized charging and discharging power curve of a typical node with 100% penetration is depicted in Fig.5. It can be observed from this figure that EVs frequently charge at 1:00-07:00 ,15:00-17:00 and 23:00-24:00, and discharge at 18:00-22:00, suggesting a important role of shifting peak loads on the lag, and avoiding additional charging loads to the power grid at rush hours.

The table II reports that optimized charging and discharging power of EVs can reduce mean square deviation of equivalent loads. Comparing optimized charging and discharging with randomly charging, the mean square deviation of equivalent loads reduces by 65.9%, and the active losses reduce 57kWh with 50% penetration. With 100% penetration, it reduces the active losses of 101 kWh, saving the electric energy of 36865kWh and approximately ¥18800 according to the current electrovalence of ¥0.51/kWh. As the number of EVs increases, dispatching EVs' charging and discharging will produce greater economic benefits.

Furthermore, optimized charging and discharging can improve the level of the bus voltage. With 100% penetration, the amplitude of the node voltage between 1:00 and 20:00 is depicted in Fig. 6.

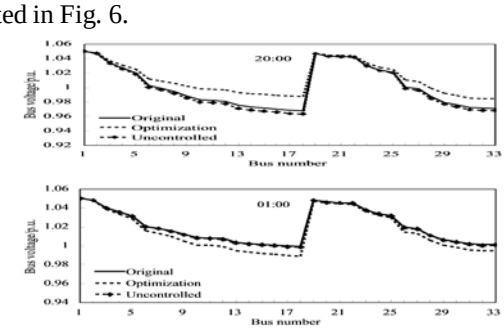

Figure 6. The node voltages of system with 100% penetration

TABLE II. THE MEAN SQUARE DEVIATION OF EQUIVALENT LOADS AND THE ACTIVE NETWORK LOSS OF THE SYSTEM

penetration	mean square deviation of equivalent loads of randomly charging /MW^2	mean square deviation of equivalent loads via optimization /MW^2	active losses of randomly charging /MW·h	active losses via optimization /MW·h
50%	6.7724	2.3047	2.495	2.438
100%	7.1633	0.4476	2.553	2.452

At 01:00, the minimal voltage amplitude of randomly charging is higher than that of optimized charging and discharging, since the power grid dispatches EVs to charge at the moment, introducing larger charging loads and dropping the node voltage. But the PU value of the minimal voltage amplitude is 0.9892. During peak hour 20:00, the EVs discharge power to the system under the condition of optimization. The minimal amplitude of the bus voltage is 0.9876, whereas that of randomly charging is 0.9634. The minimal amplitude of the node voltage increases by 2.51%, and dispatching EVs' charging and discharging can improve the voltage amplitude of the terminal node and improve the voltage level of the system.

V. CONCLUSION

As the capacity of PV generation systems and penetration of EVs increase, new challenges will be raised to guarantee a safe and economic power grid. In this paper, the photovoltaic generation systems and EVs with the capacity of V2G operation are integrated in the distributed grid. A multi-objective optimization model is built to regulate charging and discharging of EVs, with the purpose of reducing the line losses and balancing the load distribution. The test results on the IEEE33 node system verify that the proposed model and algorithm can flat the curve of equivalent loads, reduce the reserved capacity in adjusting the peak, optimize the active power losses and provide the voltage support for the system.

ACKNOWLEDGMENT

The work presented in this paper is result of the research project Research on Key Technology of Pure Electric Vehicle and Its Application in Industry

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