IOP Conf. Series: Materials Science and Engineering **366** (2018) 012077 doi:10.1088/1757-899X/366/1/012077

Optimized Economic Dispatch of Active Distribution Network with Electric Vehicle Group

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Abstract. With increasing penetration of distributed generation system and electric vehicles in the distribution network, new active power flow management and economic dispatch are required to cope with uncertainty and intermittence. An electric vehicle (EV) group management agency is introduced in this paper in the context of Chinese electricity market, considering the flexibility of EVs and distributed generations (DGs). An active distribution network (ADN) coordination optimal dispatch model is set up to minimize the generation cost of the distribution network and the charging cost of the electric vehicles in Matlab environment. An IEEE33-bus test system model with electric vehicle group is built up to improve electric vehicle charging and discharging management. The results verify the effectiveness of the proposed method on improving the satiability and safety of the system.

1. Introduction

In order to establish a low-carbon economy, global effort has been made to promote EVs and EVs will be a new important type of load in power grids [1]. Large scale of EVs will be connected to power grids and greatly impact in the operation and planning of distribution networks [2]. As energy storage systems, EVs can also support the network and actively participate in economic dispatch technology of ADN.. Distribution system operator (DSO) can then make use of new economic dispatch technologies and coordinate power flow between DGs, loads and energy storage system (ESS) [3].

In ADN, EVs can connect to grid as distributed energy storage and can interact with power grids as "load" and "supply". With large scale EVs connected to the power grids, centralized power supply and peak load will appear in the distribution network or even cause the network congestion if there are no constraint and management of the behaviors of EVs. However, if the charging/discharging behavior of each EV was under the control of DSO, the dimensionality of variables in the optimization model will increase sharply. And the threshold power level of users participate in electricity market is MW, which cannot be reached by a small number of EVs [4, 5]. Therefore, a charging-discharging control strategy in the distribution network is needed to coordinate optimal economic dispatch, so as to make advantage of the flexible charging/discharging characteristics of EVs and generation characteristics of DGs.

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In AND, there are many kinds of DGs. Wind power and photovoltaic power are intermittent renewable energies. Micro turbine (MT) and diesel engine (DE) are controllable distributed generations (CDGs), whose power outputs are flexible and adjustable. The uncorrelated EVs and CDGs are connected through the DSO to become correlative scheduling objects. A management agency and the DSO are needed to coordination dispatch the generation of CDGs and the charging/discharging of EVs. That is to prevent the congestion caused by the large scale EVs unordered charging/discharging and ensure the safety and stability of the system operation. Controlled EV charging and discharging in ADN can improve the valley to peak of load [6], economy of power systems [7] and reduce the charging cost of EVs [8]. In practice, it is impossible for the DSO to control charging-discharging at a vehicle level, and this needs to be done at a group level (hundreds of EVs).

In this paper, an optimal dispatch model aiming to minimize the charging cost of EV group and the generation cost of the system is proposed. The chance-constrained programming theory is used to conduct the stochastic optimization. An IEEE33-bus test system model with electric vehicle group is built up to improve electric vehicle charging and discharging management and reduce the related costs.

2. Supply and demand coordination economic dispatch

2.1. ADN market structure with DGs and EV group

A bidirectional interact control system is built up in this section. As a link between DSO and the users, a charging/discharging operator can integrate the EVs charging/discharging power and provide dispatchable power electricity to power systems. EVs in aggregator is a group of EVs with near spatial distances like a housing estate or a street. The aggregator can promote the interaction between DSO and users and to realize management of the charging/discharging time of EVs by charging/discharging operators.

2.2. Operation model of DGs

Traditional objective model of DE generators is a quadratic polynomial equation related to fuel cost and active power outputs. The MT operation fuel cost functions are as equation (2) shows.

$$F_{\mathrm{DE}}(P_{\mathrm{DE}}(t)) = c_2 P_{\mathrm{DE}}(t)^2 + c_1 P_{\mathrm{DE}}(t) + c_0 \tag{1}$$

$$F_{\mathrm{MT}}(P_{\mathrm{MT}}(t)) = C_{\mathrm{MT}} \frac{P_{\mathrm{MT}}(t)}{\eta_{\mathrm{MT}}(P_{\mathrm{MT}}(t))} \tag{2}$$

$$C_{\mathrm{MT}} = \frac{C_{ng}}{L} \tag{3}$$

$$\eta_{\mathrm{MT}}(t) = m_3\left(P_{\mathrm{MT}*}(t)\right)^3 + m_2\left(P_{\mathrm{MT}*}(t)\right)^2 + m_1 P_{\mathrm{MT}*}(t) + m_0 \tag{4}$$

where $P_{\mathrm{DE}}(t)$ and $P_{\mathrm{MT}}(t)$ are the DE andMTpower outputs at time t; c_2、c_1、$c_0$are DE consumption characteristic parameters;C_{MT} and $P_{\mathrm{MT}*}$ are the fuel unit cost and the per-unit value in MT, respectively; $\eta_{\mathrm{MT}}(P_{\mathrm{MT}}(t))$ is the efficiency of MT operation. C_{ng} is the price of natural gas, and L is the low heating value. m_3、m_2、m_1、m_0 are the relation characteristic parameters of MT efficiency and power outputs.

2.3. Logical architecture of the Double layer model

As a mobile energy storage system, EVs can optimize the power system operation by storing energy and outputting power. Refer to the driving cycles, the numbers of dispatchable EV $N_{avi}(t)$ by the DSO and numbers of EV in the state of driving $N_{dri}(t)$ in time t are provided. The per kilometre energy consumption is E_{C} ,and energy consumption is $P_{dch}(t)$. The state of charge (SOC) at the start of time period $t$is $S(t)$, and the SOC at the start of time period t+1is $S(t+1)$. The related equations are given as follows.

$$N_{avi}(t)=\lambda_{acc}N_{ev}P_{avi}(t) \tag{5}$$

$$N_{dri}(t)=\lambda_{acc}N_{ev}-N_{avi}(t) \tag{6}$$

$$P_{dch}(t)=N_{dri}(t)E_{\mathrm{C}}(t)v_e(t)\Delta t \tag{7}$$

$$S(t+1)=S(t)+\frac{\eta_{ch}P_{ch}(t)\Delta t-P_{dch}(t)\Delta t}{N_{acc}B_{\mathrm{C}}} \tag{8}$$

$$P_{ch}(t)=\sum_{i=1}^{\lambda_{acc}N_{avi}}p_{ch}(i,t) \tag{9}$$

$$N_{acc}=\lambda_{acc}N_{ev} \tag{10}$$

where, N_{ev} is the number of EV; λ_{acc} is the factor of acceptable dispatch; $P_{avi}(t)$ is the driving probability; $v_e(t)$ is the driving speed; η_{ch} is the efficiency of charging and discharging; $P_{ch}(t)$ is the total charging power of lay-off vehicles. $p_{\mathrm{ch}}(i,t)$ is the charging power; N_{acc} is numbers of dispatchable EV; B_{C} is the average capacity of EV batteries.

3. Supply and demand coordination optimal dispatch model

3.1. Objective function

The minimum generation cost objective functions contains the electricity purchasing cost, producing cost of direct dispatched DGs, purchasing cost and compensation of the flexible load. The objective of charging/discharging operators is the minimum EV group charging cost. Equations are as follows:

$$\min F_1=\sum_{t=1}^{N_t}(f_{grid}(t)+f_{agent}(t))+\Delta f_{agent}+\sum_{i=1}^{N_{\mathrm{DG}}}\sum_{t=1}^{N_t}f_{\mathrm{DG},i}(t)+M_{\mathrm{DG},i}(t)+D_{\mathrm{DG},i}(t) \tag{11}$$

$$f_{grid}(t)=C_{grid}(t)P_{grid}(t)\Delta t \tag{12}$$

$$f_{agent}(t)=C_{agent}(t)P_{agent}(t)\Delta t \tag{13}$$

$$M_{\mathrm{DG},i}(t)=K_{\mathrm{MT}}P_{\mathrm{MT}}(t)\Delta t \tag{14}$$

$$\Delta f_{agent}=\lambda_{com}\max\left\{\sum_{t=1}^{N_t}(P_{agent}^0(t)-P_{agent}(t)),0\right\} \tag{15}$$

$$f_{\mathrm{DG},i}(t)=\begin{cases}F_{\mathrm{MT}}(P_{\mathrm{MT}}(t))\\ F_{\mathrm{DE}}(P_{\mathrm{DE}}(t))\Delta t\end{cases} \tag{16}$$

$$D_{\mathrm{DG},i}(t)=\frac{C_{\mathrm{az,MT}}}{8760k_{\mathrm{MT}}}\frac{r(1+r)^{n_{\mathrm{MT}}}}{(1+r)^{n_{\mathrm{MT}}}-1}P_{\mathrm{MT}}(t)\Delta t \tag{17}$$

$$\min F_2=\sum_{i=1}^{N_d}\sum_{t=1}^{N_t}C_{\mathrm{P}}(t)P_{\mathrm{ch},i}(t) \tag{18}$$

$$C_{\mathrm{P}}(t)=\alpha(t)+C_{\mathrm{S}}(t) \tag{19}$$

where, N_{DG} and N_d are the number of DG and Aggregator, respectively; N_t is the dispatchable time period; $f_{grid}(t)$ and $f_{agent}(t)$ are electricity purchasing cost from power system and controllable DG agents, respectively; Δf_{agent} means the compensation to controllable DG agents; $C_{grid}(t)$、$P_{grid}(t)$ are the ADN electricity purchasing price and power from the power system, respectively; $C_{agent}(t)$、$P_{agent}(t)$ are the ADN electricity purchasing price and power from the controllable DG agents, respectively; λ_{com} is the factor of compensation; $P_{agent}^0(t)$ is the purchasing power from controllable DG agents before the adjustment of charging/discharging service fee; $f_{\mathrm{DG},i}(t)$, $M_{\mathrm{DG},i}(t)$ and $D_{\mathrm{DG},i}(t)$ are the fuel cost, operating maintenance cost and depreciable cost of DGs, respectively; K_{MT} is the per-unit operating maintenance cost coefficient; $C_{\mathrm{az,MT}}$ is per-unit capacity installation cost; k_{MT} is the factor of MT capacity; r is annual interest rate; n_{MT} is the investment payback period of MT; $C_{\mathrm{P}}(t)$ is the charging price of EV; α is the time-of-use (TOU) power price; C_{S} is the charging/discharging service fee; $P_{\mathrm{ch},i}(t)$ is the charging power.

3.2. Constraint function

The constraint functions of power balance, EV group charging and discharging power, ESS and SOC and line power flow constraints are as follows:

$$P_{Gi,t} - P_{Di,t} - P_{\mathrm{chi},t} - V_{i,t}\sum_{j=1}^{N} V_{j,t}(G_{ij}\cos\theta_{ij,t} + B_{ij}\sin\theta_{ij,t}) = 0 \tag{20}$$

$$Q_{Gi,t} - Q_{Di,t} - V_{i,t}\sum_{j=1}^{N} V_{j,t}(G_{ij}\sin\theta_{ij,t} - B_{ij}\cos\theta_{ij,t}) = 0 \tag{21}$$

$$P_{Gi}^{\min} \le P_{Gi,t} \le P_{Gi}^{\max} \tag{22}$$

$$Q_{Gi}^{\min} \le Q_{Gi,t} \le Q_{Gi}^{\max} \tag{23}$$

$$V_{i}^{\min} \le V_{i,t} \le V_{i}^{\max} \tag{24}$$

$$P_{ch}^{\min} \le P_{\mathrm{ch},t} \le P_{ch}^{\max} \tag{25}$$

$$P_{dch}^{\min} \le P_{\mathrm{dch},t} \le P_{dch}^{\max} \tag{26}$$

$$S_{\min} \le S(t) \le S_{\max} \tag{27}$$

$$S_{need} \ge S_{need,\min} \tag{28}$$

$$S(t_0) = S\left(t_{end}\right) \tag{29}$$

$$P_{l,t} = V_{i,t}V_{j,t}(G_{ij}\cos\theta_{ij,t} + B_{ij}\sin\theta_{ij,t}) - V_{i,t}G_{ij} \tag{30}$$

$$-P_{l}^{\max} \le P_{l,t} \le P_{l}^{\max} \tag{31}$$

where, $P_{Gi,t}$ and $Q_{Gi,t}$ are the active and reactive power at node *i* and time *t*, respectively; $V_{i,t}$, G_{ij}, B_{ij} and $\theta_{ij,t}$ are the voltage amplitude of node *i*, conduction of branch *ij*, susceptance of branch *ij*, and phase angle difference of node *i* and node *j* at time *t*, respectively. For EV group, the $P_{ch}^{\max} = \lambda_{acc}N_{\mathrm{avi}}(t)p_{ch}^{\max}$, where $p_{ch}^{\max}$ is the maximum charging power of a single EV. And $P_{ch}^{\min} = \lambda_{acc}N_{avi}(t)p_{ch}^{\min}$, $p_{ch}^{\min} = -p_{dch}^{\min}$, where $p_{ch}^{\min}$ is the maximum discharging power of a single EV. S_{need} is the SOC which satisfies the EV group driving demands, and $S_{need,\min}$ is the minimum limit of S_{need}. $S(t_0)$ and $S\left(t_{end}\right)$ are the SOC at the dispatching beginning time and dispatching ending time, respectively; $P_{l,t}$ is the active power of the *l* th electric line at time *t*.

A chance constrained programming is used to conduct the stochastic simulation of the intermittent renewable energy power outputs. And a MCS-PSO (Particle Swarm Optimization based on Monte Carlo Simulation) method is used to calculate the optimal solutions [9].

4. Test results and analysis

4.1. Data information

In the modified IEEE33-bus test system with EV group, each operator administers an EV Aggregator, and the number of EV in each Aggregator is 360, 270 and 270, respectively. A battery energy storage with capacity of 800 kW•h is connected at node 7. The maximum power of battery energy storage is 0.4MW, and the initial SOC is 50%. A 300 kW diesel engine is connected at node 32 and a 300kW micro turbine is connected at node 5. Two wind turbines with 500kW capacity are connected at node 25 and node 28. A local error beta-distributed model is used to simulate the wind power outputs. Two photovoltaic generators with 500kW capacity are connected at node 15 and node 22 respectively and the illumination intensity distribution fits the Beta distribution [10].

4.2. Results analysis

There are 4 scenarios in the optimization process: Scenario I is free charging/discharging model; Scenario II is the optimal power dispatch with EV group aiming to minimize only the generation cost of the system; Scenario III is the optimal power dispatch with EV group aiming to minimize only the EV charging cost; Scenario IV is the coordination optimal dispatch aiming to minimize both generation cost and EV charging cost.In the free charging/discharging model, the EV group charging operations will be conducted randomly upon the EV owners' habits. The charging power of each Aggregator and original electricity load are shown in figure 1.In Scenario I, the peak charging power is added on the peak load, which makes the valley-to-peak change from 1580kW to 3185.33kW. The utilization efficiency of electricity resource is also decreased. However, this condition is improved after the EV group accepting the dispatch like Scenario IV shows. There is an obvious concave region in the optimal load curve in Scenario IV at peak load times. This concave region comes from the discharging operations of EV group at peak load times. The owners prefer to perform EV charging at valley load times and discharging at peak load times to reduce the charging cost, which can realize the peak and valley complementation with the original load.

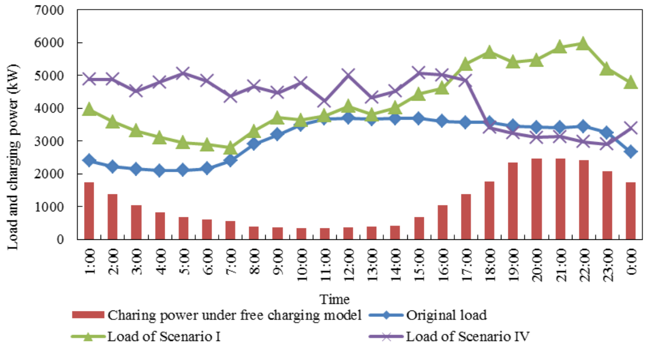

Figure 1. The charging/discharging power distribution of each Aggregator under free charging/discharging mode

The results of load rate of transmission line are shown in figure 2. In Scenario I, the branch 1 is overloaded and congestion occurs in the power system from 18:00 to 23:00. The maximum overload probability is 125%. On the contrary, the load rate from 6:00 to 10:00 is low because the EV group charging power and electricity consumption are low at this time period.

In Scenario IV, the overload of Branch 1 is reduced to under the datum line, and the system congestion problem is solved. The load rate from 18:00 to 23:00 is decreased due to the dispatchable EV group discharged to supply energy to the system to relieve the stress of transmission lines at this original peak load time period.

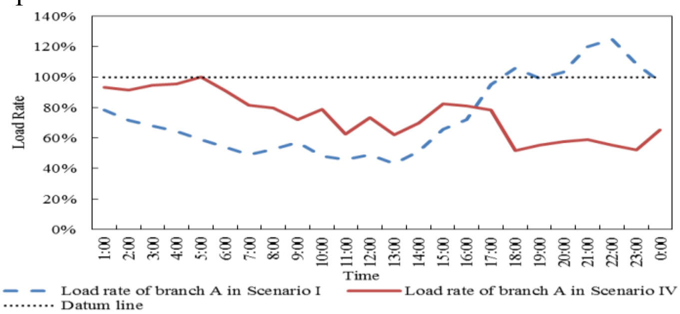

Figure 2. The load rate of Branch A

The generation cost and charging cost in different Scenarios are shown in table1. Both of the costs in Scenario IV are lower than those in Scenario I. Compared with the single-objective optimization results in Scenario II and III, the generation cost and EV charging cost in Scenario IV are higher. In order to minimize this generation cost, the EV charging/discharging strategy is restricted at some time periods to satisfy the constraints of the generation. The EV charging/discharging strategy focuses on its own benefits and the scheduling of generating units is operated passively. The results show the local conflicts of the two objective functions. Therefore, the proposed coordination optimal dispatch model that considers both generation cost and EV charging cost in the optimization problem gives the best results.

Table1. Theoptimization results

Scenario	Generation cost/yuan	Charging cost/yuan
I	6.31×10^4	4.13×10^4
II	5.72×10^4	3.96×10^4
III	6.58×10^4	3.48×10^4
IV	6.25×10^4	3.83×10^4

5. Conclusion

A supply and demand coordination ADN optimal dispatch model with EV group flexible charging/discharging response is proposed in this paper. The experiments are conducted on a modified IEEE 33-bus test system. The results show that the ADN market structure can realize the coordination dispatch more conveniently and quickly. The optimization model with multiple objectives, minimum generation cost and minimum EV charging cost, can make full use of the response capability of EV group and can also offer dispatching accepted chances to the dispatch operators, charging/discharging operators and EV owners. Four scenarios of the optimization model are given in the experiments and the test results show that the proposed coordination optimal dispatch strategy is more effective which can reduce both the generation cost and charging cost of the EV group, which can improve the positivity of EV owners participating in the power dispatch. In general, the proposed coordination multi-objective optimal dispatch model provides an optimal operating mode to the power system.

Acknowledgments

This work has been supported by the Science and Technology Project of State Grid (2017YF-27).

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