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Energy Procedia 103 (2016) 237 – 243

Energy Procedia

Applied Energy Symposium and Forum, REM2016: Renewable Energy Integration with Mini/Microgrid, 19-21 April 2016, Maldives

The Active and Reactive Power Dispatch for Charging Station Location Impact Factors Analysis

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Abstract

With the increasing number of Electric Vehicles (EVs) in modern society, a number of challenges and opportunities are presenting themselves. For example, how to choose charging station locations to minimize the Distribution Network's (DN) power loss when a large number of EVs are connected to the DN. How impact factors, such as different load patterns, EVs' charging locations and network topology, affect charging station location is becoming vital. In this paper a new charging station location methodology informed by impact factor analysis is proposed by using the Active and Reactive Power Dispatch of charging stations in terms of power loss minimization. Results for the 36 DN with three different scenarios are presented. In addition, a more realistic model based on EV's daily travel patterns is built to illustrate how these impact factors affect charging station location. It is demonstrated that the optimal charging station location in terms of power loss minimization can be found by using the new methodology, and it is not affected by the EVs' charging location and load patterns, it is affect by the network topology.

Peer-review under responsibility of the scientific committee of the Applied Energy Symposium and Forum, REM2016: Renewable Energy Integration with Mini/Microgrid.

Keywors: electric vehicle, distribution networks, impact factors, charging stations

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1. Introduction

Modern power systems are suffering pressures from government, large industries and investors. Especially when new type of loads are emerging, such as EVs. These new technologies make life easier and more comfortable. However, they also challenge the traditional power system. For example with a large level of EV penetration, are there enough charging stations to facilitate EVs' charging. How do we choose charging stations' locations, and how the impact factors such as different load patterns, EVs' charging locations and network topology affect this. This is becoming vital not only for power system operators, but also for EVs' users.

In [1] the authors developed a mixed-integer programming model to determine the optimal location of charging station by considering the EVs' parking demands, local jobs and a community's population density. In [2] the authors considered the impacts of limiting EV's full state of charge on the total charge energy for charging station planning.

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Peer-review under responsibility of the scientific committee of the Applied Energy Symposium and Forum, REM2016: Renewable Energy Integration with Mini/Microgrid.
doi:10.1016/j.egypro.2016.11.279

Reference [3] considered the environmental factors and service radius for charging station location choice by using a two-step screening method. Reference [4] proposed a new charging station model, which is influenced by the electricity consumption along the roads in cities and oil sales. Reference [5] considered how traffic flow and EVs' battery capacity affect a charging station's location choices and size.

Unlike these papers, the proposed method in this paper uses the active and reactive optimal power flow to analysis how the charging station locations change as a consequence of changing the network's resistance, reactance and EV's charging locations, which can be chosen at any bus in test 36 DN. The structure of this paper is as follows: In section two a theoretical analysis of this method is given, the charging station structure and the base case are also introduced for the cases studies and the results are discussed. In section three, two cases based on several scenarios are given and simulation results are discussed. In the final section, the conclusions of this paper are given.

2. Theoretical Analysis

The main focus of this paper is to analyse how the impact factors such as loads and network resistance and reactance affect optimal charging station location choice in terms of power loss minimization. In order to quantify the impacts on the DN, the optimal charging station location was obtained by using the active and reactive power approach. The EV to grid concept is not considered in this paper.

2.1. Charging Station Introductions

The charging station plays an essential role in EVs' power supply chain. It consists of a Battery Energy Storage System (BESS), which can not only provide the energy to EVs, but also can provide energy to local electricity customers. The BESS consists of batteries and Power Conditional Systems (PCS) [6][7].

A PCS has several electronic devices such as capacitors, diodes and transformers, the structure can be seen in [6].

It has two operation modes. The first operation is called discharging mode. In this operation mode BESS is being discharged to supply the active and reactive power to loads. The second operation mode is called charging mode. In this operation mode BESS is being charged, absorbing both active and reactive power from the DN. The active and reactive power discharge of the BESS should not exceed the maximum apparent power S_{ESSmax} of the BESS [8][9].

$$P_{dis}^2 + Q_{dis}^2 \le S_{BESSmax}^2 \tag{1}$$

$$P_{char}^2 + Q_{disc}^2 \le S_{BESSmax}^2 \tag{2}$$

The active power for charging and discharging must be positive values

$$P_{char(k,h)} \ge 0, \qquad P_{dis(k,h)} \ge 0 \tag{3}$$

$$S_{ESSmax(k,h)}^2 \ge Q_{dis\,(k,h)} \tag{4}$$

Moreover the upper and lower bound of the storage capacity should satisfy

$$E_{min} \le E_{Low}, \qquad E_{Up} \le E_{max} \tag{5}$$

The EVs power demand at each time slot can be calculated by using the equation

$$P_i(t) = \frac{[b_i - x_i(t)] \times C_i}{E_i \times H_{charging}}, \forall i, t \tag{6}$$

where $P_i(t)$ is the power demand of EVs at any time slot. b_i is the desired State of Charge (SOC) in this paper is 100%. $x_i(t)$ is the SOC at the beginning of t is 20%. C_i is the capacity of EV. E_i is the battery charging efficiency of EVs, $H_{charging}$ is the average charging period of all four types of EV. It is assume one charging station can charge 100 EVs simultaneously [10].

2.2. Base case and model explanation

The base case is the original network in this paper. It is the 36-bus DN [11] without any modifications, and it is assumed that there are two charging stations in the DN, charging station one's has already been installed in bus two because the system largest loss occurs there. The 36-bus DN voltage is 11KV and the total active reactive load are 3.97MW and 2.08Mvar. The system's topology is shown in Fig.1 and reference [11]. Also in order to analyse the power flow between each busbar, a simple π line model is built and shown in Fig.2.

The objection function is built to find the charging station two's station.

$$f_j = \sum_{i=1}^{j} R_{1i(j)} |P_i' + jQ_i'|^2 \qquad j = 3,4,5 \cdots\cdots N \tag{7}$$

where $P_i' = P_{dis2} + P_{load2} + P_{m2F} - P_{grid} - P_{dis1}$ (8)

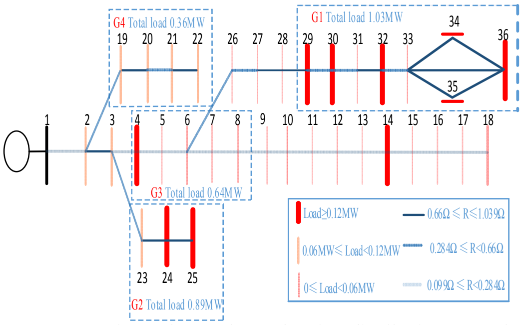

Fig.1. The topology of 36-bus distribution network

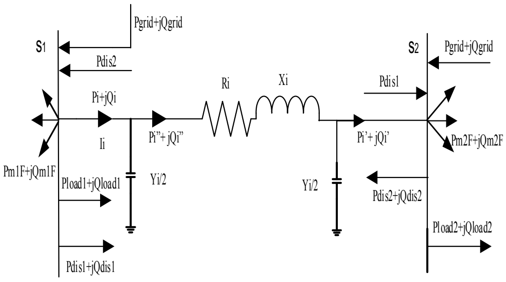

Fig.2. Power flow analysis

$$Q_i' = Q_{dis2} + Q_{load2} + Q_{m2F} - Q_{grid} - Q_{dis1} - V_{s2}^2 \frac{Yi}{2} \tag{9}$$

The goal is to find the optimal location for charge station two, where equation (10) reaches the minimum value.

$$F_m = Min f_j \tag{10}$$

The $R_{1i(j)}$ is the resistance between two charge stations. N is the test system's total bus number. P_{load2} is the load at bus S_2. P_{m2F} is active power injection from bus S_2.

$$Min\ P_L = \sum_{\forall s_1, s_2}^{s_1, s_2 \in S_B} I_i^2 R_i = \sum_{\forall s_1, s_2}^{s_1, s_2 \in S_B} \left(\frac{P_i^2 + Q_i^2}{V_{s_1}{}^2} \right) R_i \tag{11}$$

$$P_i = P_i' + R_i \frac{P_i'^2 + Q_i'^2}{V_{s2}^2} \tag{12}$$

$$Q_i = Q_i'' - V_{s1}^2 \frac{Yi}{2} = Q_i' + X_i \frac{P_i'^2 + Q_i'^2}{V_{s2}^2} - V_{s1}^2 \frac{Yi}{2} \tag{13}$$

The active and reactive power flow in π line model must satisfy the Kirchhoff's current law.

3. Case Study and Result Discussion

In this section, two cases base on 36-bus DN are analysed. The first case is without any EVs charging, how the network's loads, resistances and reactance's changes affect charging station two's locations. The second one is with EVs charging, how EVs' charging locations change affect charging station two's location.

3.1. The Base Case

Before analysing the first and second case, the optimal charging station location for station two needs to be found by using the proposed method in chapter 6. Because if we know the optimal charging station location, then we can analysis how the impact factors affect the optimal location. It is installed in bus 32. The objective function's values and real system power loss are shown in Fig.3 and Fig.4.

The simulation results are shown in Fig.4. It is proved that the optimal location for charging station two is bus 32. Regarding to the objective function's values and simulation results. In general, the heavier load demands of test system, the relative further from station one, the lower power loss and objective functions we have. For example bus 32 is in the system largest loads area G_1, installing station two in the larger loads area can cause lower power loss than small loads area.

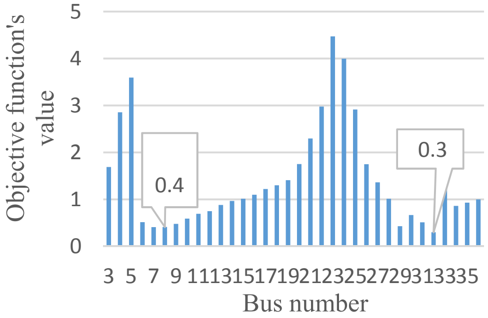

Fig.3. Objective function’s values of 36-bus test DN

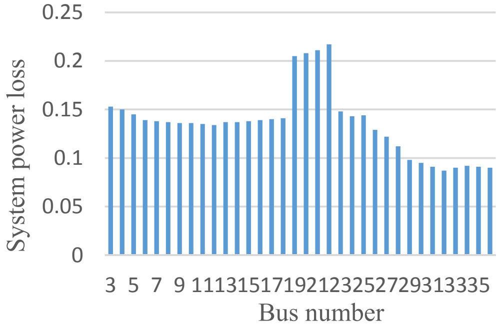

Fig.4. Power loss of the 36-bus test DN

3.2. The First Case

The first case is without any EV penetrations, how loads, resistance, and reactance change influence the optimal location of charging station two. It has three scenarios. The first scenario is to change the test system’s resistance, keep load as the original system’s loads. The second scenario is to change the test system’s loads, keep resistance as the original system’s resistance. The third scenario is to change the test system’s resistance, meanwhile change system’s loads.

In the first scenario the resistances and reactance between bus 9 to bus 18 and bus 29 to bus 36 are changed to the new resistance. The system’s loads keep the same as original one. The 36 bus test-system with the changed *R* and *X* parameters shows in Fig.5.

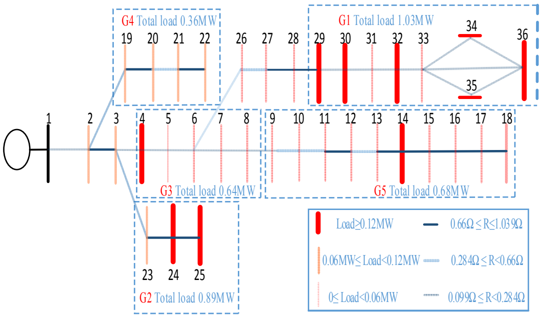

Fig.5. 36-bus test-system with changed R and X

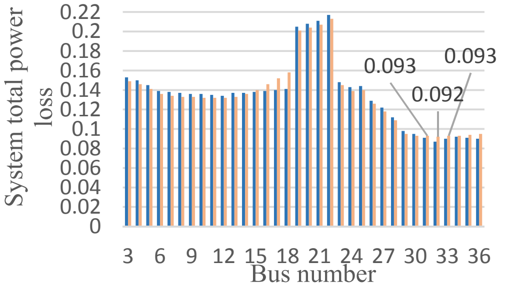

Fig.6. Total power loss comparison for the first scenario

From simulation results shown in Fig.6. The blue one is system original power loss at each bus. The yellow one is the changed system’s power loss at each bus. Although the *R* and *X* have changed, the optimal location for charge station two is still the same. Regarding to this scenario, increase system’s R and *X* between bus 9 to bus 18 and decrease bus 29 to bus 30, rise the total power loss at each bus between bus 15 to bus 18 and bus 31 to bus 36. But the charging station two’s location is not changed. Therefore, only change system’s *R* and *X* in area G_1 and G_5 , the optimal location of charging station two is not influenced. In the second scenario the system’s loads from bus 11 to bus 18 and from bus 29 to bus 36 are changed to new loads. The system’s *R* and *X* keep the same as original one.

From simulation results shown in Fig.7. The yellow one is the new system’s power loss at each bus. Increase the load at each bus between bus 11 to 18 to original one’s four times and decrease the load at each bus between bus 29 to 36 to original one’s four times, rise the total power loss, but the optimal location for charge station two is still the same which is bus 32. Therefore, only change the system loads in area $G_1$and G_5, the optimal location for charge station two does not change.

In the third scenario the system’s loads from bus 11 to bus 18 are changed to new loads. Meanwhile, the system’s *R* and *X* between bus 9 to bus 18 and bus 29 to bus 30 are changed to the new values.

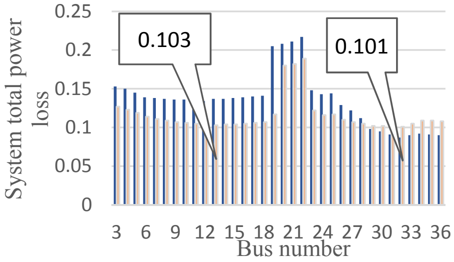

Fig.7. Total power loss comparison for the second scenario

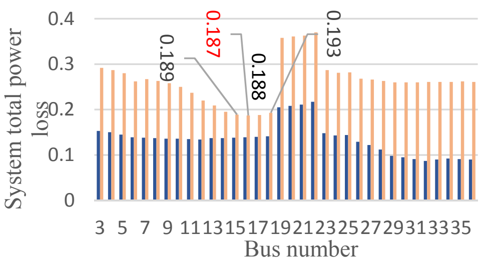

Fig.8. Total power loss comparison for the third scenario

From simulation results shown in Fig.8, we can see the blue one is system original power loss at each bus. The yellow one is new test-system's power loss with changed loads, R and X. For new test system the optimal location of station two has changed to bus 16.

The previous secured charge station two's location which is bus 32 has moved to bus 16 in the third scenario. This illustrates the station two's optimal location is influenced by changing both system loads, R and X simultaneously. If only change one of them the location will not change. Also in this third scenario the optimal location tends to near heavy loads and big resistance. Which means install charge station two in the bus between bus 11 to 18, the power loss will be smaller than the other buses Overall, the much heavier loads and higher system R and X the bus has the higher possibilities it can be chosen to be the optimal location of charging station two. However, in the real DN the line parameters, such as R and X are hardly changed. Therefore more realistic scenarios are given in the second case.

3.3. The Second Case

The main aim for the second case is to test changing the system loads and EVs' charging locations the optimal charge station's locations can be affected or not. Two scenarios are developed for this case.

In the first scenario, EVs can charge at any time between 9:00 to 17:00. According the national travel survey statistics and daily load profile [12][13],between 7:00 to 9:00 people leave their homes from G_5 area to working places G_1 area and start working. In Fig.9 it assumes that G_5 is the residential area because the loads are much lighter than G_1, during the period between 9:00 to 13:00. In this case, it is also assumed that EV charging place is randomly chosen in G_1 area.

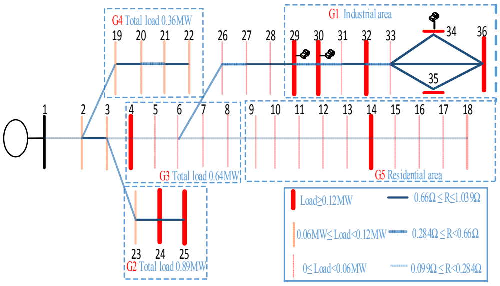

Fig.9. The first scenario Charing pattern

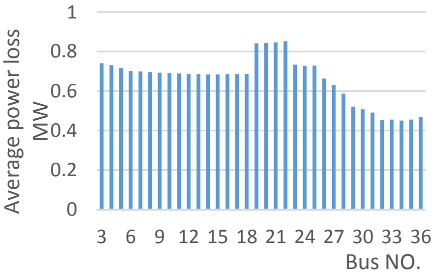

Fig.10. Average power loss for test DN during the period 9:00 to 17:00

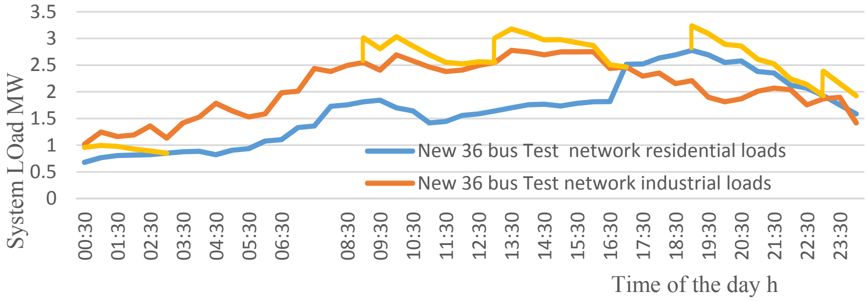

Fig.11. Network's load profiles after adding EVs' load between 9:00 to 17:00

In order to prove the best location for charge station two in terms of power loss minimization is bus 32. The EVs are charged in the G1 area randomly during the daytime. Two cases for the daytime charging are listed below:

Case 1. The EVs 'charging starts at 9:00 and finish at 13:00, In order to simulate hourly power loss of the whole test network, the two different load patterns, which are the industrial load pattern, residential load pattern and EVs loads are scaled in Fig.11 [14]. All 100 EVs are charged in the G1 area during the period between 9:00 to 13:00. In this case, these EVs start charging at 9:00 in the morning and finish at 13:00 in the afternoon. These EVs' power demands increase the industrial loads profiles, which can be seen from Fig.11. After 13:00 EVs are fully charged, and a new charging recycle starts from 13:00 to 17:00. Meanwhile, the residential load profiles do not change. Case 2. The EVs charging starts at 13:00 and finish at 17:00.

Fig.10 shows the average power loss for 36-bus test network in the period between 9:00 to 17:00. From the simulation results we can see the optimal location for charge station two is bus 32, which proves the method used in this paper. Although the EVs are charged randomly in the industrial area, the bus 32 is still the optimal location for charge station two in terms of power loss minimization. It is proved that the loads profile change, the optimal charge station two's location does not change.

In the second scenario, EVs can be charged at any time between 19:00 to 24:00 according to the national travel survey [12]. Because most of people do not use their vehicles during this period. In this scenario people go home from their working places, which is from G_1 area to G_5 area. These EVs are charged randomly in G_5 area.

The simulation results for average power loss of the 36-bus test network shows that, in the first charging pattern (the day time charging pattern) the average power loss is higher than the second charging pattern (the night time charging pattern). The reason for this is that in day time charging pattern, EVs are connected in industrial area, in night time charging pattern EVs are connected in residential area. Comparing the two patterns' total base loads (industrial's loads plus the residential loads) the day time charging pattern's base loads are much higher than the night time one. That makes average power loss of the first charging pattern higher than the second pattern. However, irrespective of the charging pattern bus 32 is always the optimal location for charge station two.

From above two different charging patterns' simulation results, we can see the optimal location for charge station two is bus 32. This proves whether EVs are charged in the industrial area or in the residential area, installing charge station two in bus 32, the total system's power loss can reach the lowest point. In other words, the EVs' location change and load patterns change will not influence charge station two's location.

4. Conclusions

In this paper, we used active and reactive power dispatch for analysing how impact factors such as different loads patterns, EVs' charging locations and network parameters affect charging station location choice for power loss reduction. It has been shown that the charging station's location is not affected by the individual changes of these impact factors. It was affected by changing the network's resistance, reactance and load patterns simultaneously. This was shown by testing the 36-bus distribution network with EVs' penetrations.

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