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GENETIC ALGORITHM FOR OPTIMAL LOCATION OF ELECTRIC VEHICLE CHARGE STATION

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ABSTRACT

With increasing number of Electric Vehicles(EVs) ,more attention is being paid to EV's charge stations. These stations play an essential role in EV industry chain.Choosing the optimal locations for these stations is becoming vitally important. Not only for power loss reduction,but also for power system security. In this paper a novel optimal charge station location method is informed based on active and reactive power flow analysis by using Genetic Algorithm (GA) in terms of power loss minimization.Results for the36-bus Distribution Network (DN) are presented.It is demonstrated that installing three stations in optimal locations in the tested network, power loss reduces by 0.088 MW, compared with the situation with two stations.

Keywords: charge stations'location, EVs, active and reactive power flow analysis, GA optimisation, power loss reduction.

NONMENCLATURE

Abbreviations

EV	Electric Vehicle
GA	Genetic Algorithm
DN	Distribution Network
BESS	Battery Energy Storage System
DG	Distribution Generation
PCS	Power Conditioning Systems
DS	Distribution System
SOC	State of charge

1. INTRODUCTION

Electric vehicles(EVs) are becoming cheaper and less environmentally damaging alternatives, to traditional vehicles. However a great number of EVs charge simultaneously can increase the Distribution Systems(DSs) power losses significantly[1][2]. How to reduce the power losses cased by these EVs is being paid more attention than before.

Previously, some researchers optimized capacitors' locations in Distribution Networks (DNs) by using planning method to reduce the power losses[3]. Ref.[4] used phase load balancing method by removing load imbalances in the radial network for loss reduction. Ref.[5][6]concentrated more on the optimal planning and economic aspects of a charge station for EV; by considering various costs, to achieve comprehensive cost and energy loss minimization.Ref.[7] considered optimal scene method to simulate the randomness of DG and load to reduce power loss in DNs.

Unlike these methods,the proposed method in this paper uses Genetic Algorithm (GA) based on power flow analysis to find the optimal locations for charge stations for power loss reduction in tested 36-bus DN.The structure of this paper is as follows: In section two theoretical analysis is given, the DN modeling, EV power demand modelling and charge station structure are also introduced. GA is used for the case studies and results discussion. In section three, a 36-bus DN with one charge station is used as case study and the GA simulation results are discussed. In the final section, the conclusions of this paper are given.

2. THEORETICAL ANALYSIS

2.1 System Modeling

2.1.1 Distribution Network Modelling

This paper uses 36-bus DN [8] without any modifications as the tested network.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.

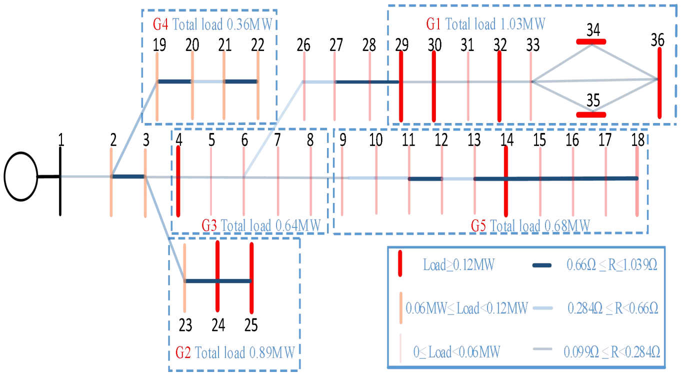

Fig 1 The topology of 36-bus distribution network

2.1.2 Electric Vehicle Modelling

The power demand of each type of EV can be calculated by using Eq. (1) [9].

$$P_i(t)=\frac{[b_i - x_i(t)]\times C_i}{E_i T_{aver}}\ \forall i,t \qquad (1)$$

where $P_i(t)$ is the power demand of the EV at any timeslot t. b_i is the SOC of EV's battery. $x_i(t)$ is the SOC at the beginning of t. C_i is the capacity of the EV. E_i is the battery charging efficiency of the EV, H_{aver} is the EV's average charge time.The total power demand of all EVs can be express as shown in Eq2.

$$P_T(t)=\sum_{n=1}^{n} P_{i(t)c}+\sum_{i}^{n} P_{i(t)n}+\sum_{i}^{n} P_{i(t)p}+\sum_{i}^{n} P_{i(t)t} \qquad (2)$$

where $P_T(t)$is the total power demands of all types of EVs. $P_{i(t)c}$, $P_{i(t)n}$, $P_{i(t)p}$, and P_{itt} are the power demand for each type, i.e. Chevrolet, Nissan Leaf, Prius, and Tesla.

Table 1

Characteristic of the EV

EV Types	Level 1 Charge		Level 2 Charge		DC Fast	
	Power Demand	Time	PD	Time	PD	Time
Chevrolet Volt	0.96-1.4 kw	5-8 hours	3.8kw	2 hours	n/a	n/a
Nissan Leaf	1.8 kw	12-16 hours	3.3kw	7 hours	50kw +	15-30 m
Prius	1.4kw (120v)	3 hours	3.8kw (240v)	2.5hours	n/a	n/a
Tesla Model S	1.8kw	30+ hours	16.8 kw	4 hours	n/a	n/a

2.1.3 Charge station Modelling

The combined Battery Energy Storage System (BESS) charge station is different compare with the traditional charge station. Traditional stations are not able to store off-peak energy and sell it to EVs and local residents at any time. Whereas, BESS can make the profits by utilizing electricity price differences between peak and off-peak times. The configuration of the stations can be seen in Fig.2.

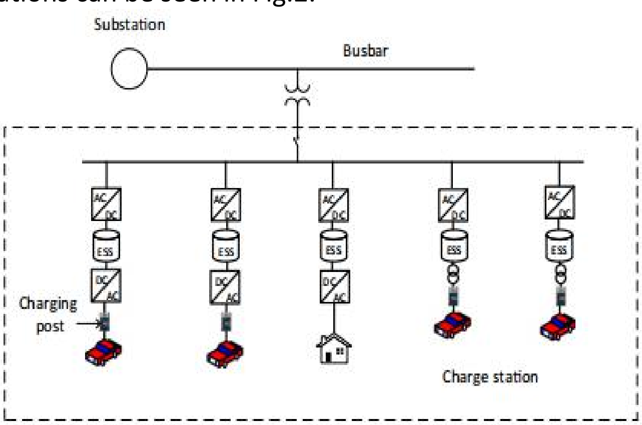

Fig 2 Charge station's configuration.

The charge station consists of BESSs, normal charging points and relevant charging facilities such as transformers, active and reactive compensators, inverters and converters, and charge paces.The BESS consists of batteries and Power Conditioning Systems (PCS)[10][11].A simple PCS consists of electronic devices such as capacitors, diodes and transformers, Based on the independent and rapid control capability of the PCS, active discharge and reactive power dispatch were set as controlled variables when identifying charge station's optimal location. It is noted that active power can be either charging or discharging at any given time.

2.2 Genetic Algorithm Implementation

GA is the most widely used artificial intelligence for optimisation. It has been used in power systems to solve power flow calculations, economic dispatch, and unit commitment. GA is used in this paper to find the optimal locations for charge stations because it is designed for solving large-scale optimisation problems and can be much quicker than the conventional mathematical optimisation methods.

The goal for GA is to find the best charge stations' locations to minimize network power loss. The fitness function based on active and reactive power flow is shown in Eq. (3).

$$f_j = R_{1i(j)} \left| P_i^{'} + jQ_i^{'} \right|^2$$
$$j = 3,4,5 \cdots\cdots N; i = 3,4,5 \cdots\cdots N \quad (3)$$

$$P_i^{'} = P_{dis2} + P_{load2} + P_{m2F} - P_{grid} - P_{dis1} \quad (4)$$

$$Q_i^{'} = Q_{dis2} + Q_{load2} + Q_{m2F} - Q_{grid} - Q_{dis1} - V_{s2}^2 \frac{Y_i}{2} \quad (5)$$

Where $P_i^{'}$ and $Q_i^{'}$ are the injection active power and reactive power to bus S_2 respectively [12]. *fj* is the fitness function of GA.The The $R_{1i(j)}$ is the resistance between two charge stations. *N* is the test system's total bus number. P_{dis} and Q_{dis} are the active and reactive discharge power of station. P_{load2} is the load at bus S_2. P_{m2F} is active power injection from bus S_2. The series impedance and shunt admittance between bus S_1 and S_2, are $(R_i + j X_i)$ and *Yi/2* respectively.The variables are $P_{dis2} = x_1$, $Q_{dis2} = x_2$, $P_{m2F} = x_3$, and $Q_{m2F} = x_4$. GA is used to decide charging station two' s optimal location for power loss minimisation. The GA setting is shown in table 1 below:

Table 1 GA's setting

Population size	300
Crossover Probability	0.8
Mutation Probability	0.2
Stall Generations	300
Current iterations	100

3.CASE STUDY AND RESULT DISCUSSION

In the case study, there are only two charge stations in the test 36-bus DN. The first charge station has already been installed in bus two because the largest power loss occurs between bus one and bus two[12]. The same 36-bus test DN, used in reference[12], is chosen and shown in fig.3.

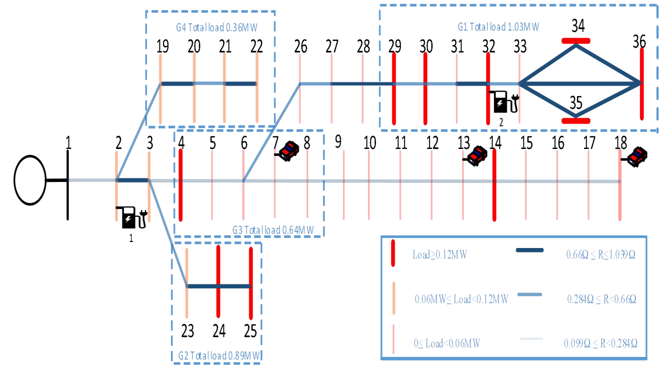

Fig 3 The topology of36-bus distribution network

The GA results can be seen from fig.4 and fig. 5. The EVs are connected to bus 7, 13 and 18 randomly; as can be seen from fig.3. From fig.4 it can be seen that the optimal location for charge station two is bus 32.

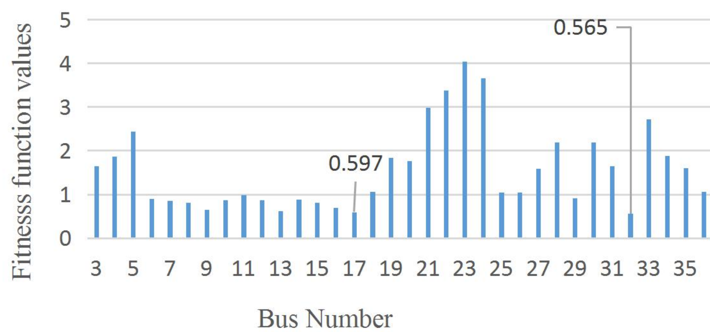

Fig 4 The fitness function's values of36-bus DN

Fig. 5 shows the best and mean fitness values and average distance between each individual in the GA. They were obtained by using the GA settings in table 1. Fig. 5 upper plot shows the best and mean fitness values coincide at the same point at generation number 55: after this number, the best fitness and mean fitness values are the same. The GA has found the best solution to the problem.

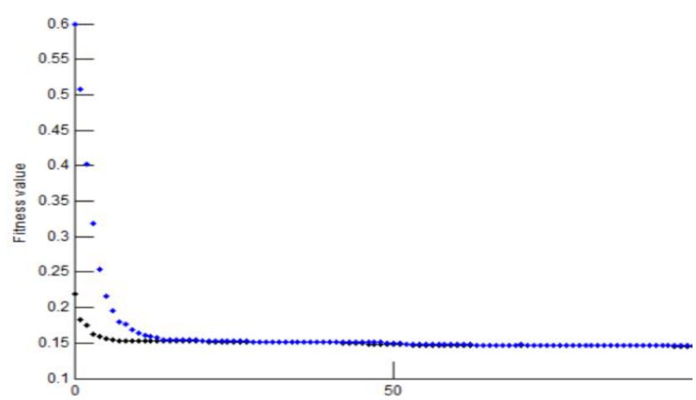

Fig 5 Fitness value of default settings(Upper plot)

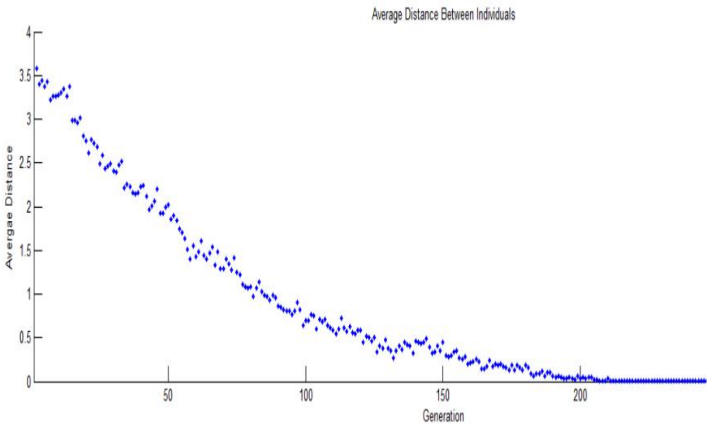

Fig 5 Fitness value of default settings(Lower plot)

From the lower plot in fig.5, we can see that around generation 230, the average distance between individuals becomes zero, which means all the individuals are the same. The best solution has been found. The average distance between each individual also shows the diversity of the population. If the average distance between individuals is large, then the diversity is high. If the distance is small, the diversity is low. Getting the right amount of diversity is very important for using GA. If diversity is too high or too low, the GA might not perform well. fig. 8.4 shows the best and mean fitness values, and average distance between each individual in the GA.

Installing reasonable numbers of charge stations can significantly decrease the test DN's power loss.By using the same method, installing three stations in optimal locations in the tested network, power loss reduces by 0.088 MW, compared with the situation with two stations. Compared with installing three charge stations, with six charge station, power loss is much lower.The network power loss reduces by 0.84MW when three more stations are installed in the network.

4.CONCLUSIONS

In this paper we used a novel GA method base on active and reactive power flow analysis for charge station location optimisation for power loss reduction.This method was tested in 36-bus DN,it has been shown that install three charge stations in optimal location the power loss can be reduced by 0.088MW. By installing three more charge stations in the tested DN 0.84MW power loss can be decreased.

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