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Evolutionary Programming Based Technique for Plug-in-Hybrid Electric Vehicle Charging System

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ABSTRACT

In the era of millennium, the electric vehicle (EV) has a high demand from many sector which is to replace the existing internal combustion vehicle since it has given a negative side impacts towards the environment and also due to the increasing of the price of the fossil fuels that decreasing day by day. The electric vehicle is one of the alternative way to reduce pollution by moving the electric vehicle by using the energy that stored in the battery's car and after the battery has reach its limit, only then the petroleum will continue the role of the energy to move the electric vehicle. The energy that required by the battery's car are generated from the charging station which it connected to the distribution network. The charging or discharging of the electric vehicle could cause some power quality issues in a few terms such as voltage profile, power losses etc. This paper presents the Evolutionary Programming Based Technique for Plug-In-Hybrid Electric Vehicle Charging System. The proposal technique has been tested on the IEEE 33-bus distribution system. The results shown that the proposed technique managed to maximize the voltage level in the system in the plug-in-hybrid electric vehicle charging system environment.

Key words : battery capacity, evolutionary programming, plug-in-hybrid electric vehicle

1. INTRODUCTION

The electric vehicle car was introduced due to the limited non-renewable energy such as petroleum and natural gas that reducing and have a high demand from the consumer day by day. Other than that, there are a lot of benefit by implementations of plug-in-hybrid electric vehicle which one of it is can reduce pollution. The pollution that caused by the internal combustion vehicle releasing polluted gaseous such as carbon monoxide, sulfur dioxide and nitrogen dioxide into the earth's atmosphere which can cause environmental damage. Nowadays, the electric vehicle are more preferable by government and enterprises because the characteristics of the electric vehicle which are energy saving and environmental protection. Based on [1], electric vehicle not only minimizing the production of carbon dioxide and other pollution gas which can lead towards a great impacts on climate but it also can change the environment into a healthier atmosphere for the citizens to live in the less pollution environment. In [2], it is proved by a several researchers that the implementation of electrification transport sector cause a great reductions amount of production greenhouse gas emission. On the other hand, the electric vehicle was introduced due to increasing cost of fossil fuels. Based on [3], the plug-in-hybrid electric vehicle was a good solution to reduce the usage of fossil fuels and the emission of greenhouse gas which also has reduced the usage of fossil fuels by 70% compared to conventional vehicles. The plug-in-hybrid electric vehicle is the best solution compared than other existing electric vehicle such as electric vehicles (EVs) and conventional hybrid electric vehicle (HEVs). In [4], the researcher has stated that EVs has a very efficient energy and zero tail pipe emission but EVs are too costly to own by consumer, lack of charging station, the weight of the batteries and it also has reduced the load capacity in the transmission network. The HEVs are more upgraded compare than EVs which it has a low emission, improved fuel economy and it used the existing fuel structure but the technology of HEVs are still fully depending on the petroleum to charge the battery pack. Then, PHEVs was introduced which to restructure other electric vehicle disadvantages. The PHEVs has attracted the consumer because it has use both electrochemical energy storage. Every plug-in-hybrid electric vehicle required a charging station which allows the PHEVs have a connection with the electric grid via plug to absorb/inject energy from/to the grid network system. Somehow, the charging of plug-in-hybrid electric vehicle could give negative side effects toward distribution network such as the increasing of power loss, voltage deviation and other power quality factor. Based on the research in [3], the large amount of load by PHEV could cause undesirable peak, the price will increase, and the reserve margins will reduced. Charging and discharging of PHEVs should be controlled or scheduled so that it won't give a big impact or negative side effects towards the distribution network. In [5], the simulation is conducted on two situation which is uncoordinated charging and coordinated smart charging. From the simulation, the results have proved that the coordinated smart charging are rarely have an impact toward the distribution network while uncoordinated charging will produce losses which are not negligible. The coordinated charging of PHEVs are very important which is to reduce the power loss and voltage drop in the distribution system.

All the issues of charging PHEV's can be prevented or minimized by using the optimization method such as backtracking search algorithm (BSA), Grey Wolf Optimizer (GWO), Particle Swarm Optimization (PSO), Artificial Bee Colony (ABC) and more. There are a few researches that have been conducted by researchers that have proved that all the optimization methods above can mitigate or minimized the power quality issues regarding to the charging of PHEVs. Based on [6], two method of optimization has been used in the research which are Genetic Algorithm (GA) and Particle Swarm Optimization (PSO). The both optimization techniques were used to find the optimal station to install the charging station without affecting the distribution systems. A result has proved that both methods has minimized the stress in distribution network after installing a few charging stations in the distribution network. In [7], two method also has been used in the research to study the energy management of the PHEVs which it is Genetic Algorithm (GA) and Enhanced Ant Colony Algorithm (EACA). The essential objective of this research is to control the parameters by using these two optimization techniques. Each optimizer has different function in this research where Genetic Algorithm (GA) is used to overcome the low solution precision while the Enhanced Ant Colony Algorithm (EACA) is used to solve slow computational speed problem.

2. METHODOLOGY

In this section, the PHEV characteristic in terms of battery capacity and number of vehicles per house also the optimization method that have been proposed will be elaborate more.

2.1. PHEV Characteristic

Every PHEV will require a battery to charge/discharge energy from the distribution network [8]. Thus, the capacity and size of the battery play an important role for PHEV. In [9], the authors has state that every different type of PHEV will have differ battery capacities and average of energy consumption of. After all the energy in the PHEVs has reached the maximum usage, the gasoline in the PHEV will replace the role of energy to move the PHEV.

So it is important to know the capacity of the battery which it is better if the movement of the PHEV are generate by the energy stored in the battery rather than the use gasoline. Based on [10], the quantity of charging PHEV in the distribution network does give an implication towards the distribution which the higher quantity of the charging PHEV in the distribution network, the higher the load in the distribution network that could cause negative effects to the distribution network.

Based on Table 1 which is obtained from [11], it shows the rate of charging the electric vehicle. For slow or normal rate of flow of charging the EV takes about 6 hours which the apparent power is 3.6 kVA and the charging method for slow/normal type charging is through the AC single phase, 230V up to 16 A. For medium/fast type charging take about 1 to 3 hours and the apparent power is 11 kVA to 20 kVA. The charging method for the medium/fast is same as the slow/normal type charging and what differentiate it is 3 phase and the current is 32A. The last charging mode of electric vehicle is fast charging which only take less than 1 hour with high apparent power which higher than 20 kVA and the charging method for fast charging type is DC off-board charging. DC off-board charging is also known as level 3 charging which on the opposite it link straight to the car's battery and it enable the off-board equipment to have any power needed. The DC fast charging stations accommodate generally more than 120 kW that is able to charge 80% of the electric vehicle (EV) less than 20 minutes and it also allow the high power DC current connected directly to the battery without going through the on-board AC/DC converter. Off-board charging also can get rid of weight from the vehicle. The higher the rate of energy transfer, the higher the vehicle conductivity required. The off-board charging also can manage the battery heating.

Table 1: Charging mode of EV

Type	kVA	Charging Time	Charging Method
Slow/Normal	up to 3.6	6 hours	AC 1ph, 230V up to 16A
Medium/Fast	11 - 20	1 - 3 hours	AC 3ph, 230V up to 32A
Fast	≥ 20	< 1 hour	DC off-board charging

Table 2: Battery capacity of all-electric ranges of PHEV

AERS Type	Percentage	Battery capacity of various PHEV types (kWh)			
		Compact sedan	Mid-size sedan	Mid-size SUV	Full-size SUV
PHEV 30	21%	7.8	9.0	11.4	13.8
PHEV 40	59%	10.4	12.0	15.2	18.4
PHEV 60	20%	15.6	18.0	22.8	27.6

Table 2 obtained from [12] shows the capacity battery from all electric ranges which every PHEV carried a different percentage of daily mileages. The higher the capacity of the PHEV battery, the longer time taken for the battery to generate energy for the movement of the PHEV.

2.2. Optimization of voltage profile and power losses

The proposed optimization technique is implemented to minimize the voltage profile in the distribution network after the plug-in-hybrid electric vehicle connected to the distribution network for charging/discharging condition. In this study, the IEEE 33-bus data are used to verify the applicability and efficiency of the proposed algorithm. The main objective function is:

$$f = \min\left(P_{losses}, V_p\right) \quad (1)$$

where:

P_{losses} – Total active power loss

V_p – Voltage profile

The active power losses and the voltage profile will be optimized after the proposed algorithm method has been applied.

$$xPn = rand\left(1,1\right) \times 10 \quad (2)$$

where:

xPn – Load at 33 bus distribution system

Every objective function should have a limit constraint and fulfil the limit constraints. Thus, the voltage constraints are as follows:

$$V_{i-\min} \leq V_i \leq V_{i-\max} \quad (3)$$

where, V_i is the root mean square (RMS) value of the i^{th} bus voltage, $V_{i\text{-}min}$ and $V_{i\text{-}max}$ are the minimum and maximum voltage profile limit at i^{th} bus.

2.3. Evolutionary Programming

Evolutionary programming is based on L.J Fogel's research which it is to develop artificial intelligence through simulated evolution. Evolutionary programming is based on an adaptive behavior simulation in evolution [13]. While evolutionary programming aims to imitate natural evolutionary processes with GAs and GP, it differs substantially in that EP emphasizes the development of behavioral models rather than genetic models [14]. The evolutionary programming applies iteratively to two evolutionary operators, namely variation and selection by mutation operators. In the evolutionary programming, there are five main components which are initialization, mutation, evaluation and selection.

The initialization in the evolutionary programming are equivalent with other EC paradigms which to initialized a population of individuals to optimized the problem. The mutation components in the evolutionary programming the main purpose of the mutation operator is to introduce population variation in order, for example, to produce new candidate solutions. Every parent produces one or more children by the mutation operator. Developing a number of evolutionary programming mutation operators.

Next is the evaluation components in the evolutionary programming which the fitness function are used to quantify people's behavioral error. The fitness function provides an absolute fitness measure to indicate how well the problem is solved by the individual, the survival in evolutionary programming is usually based on a relative fitness measure. A score is calculated to evaluate how well an individual compares with a group of competing individuals randomly selected. Persons surviving the next generation are chosen based on this relative fitness.

Consequently, the search process in evolutionary programming is driven by a relative fitness criterion and not by an absolute fitness measure, as most EAs do. The main function of the selection operator is to choose the surviving individuals for the next generation. Selection is a competitive process where parents and their offspring compete against a group of competitors to survive.

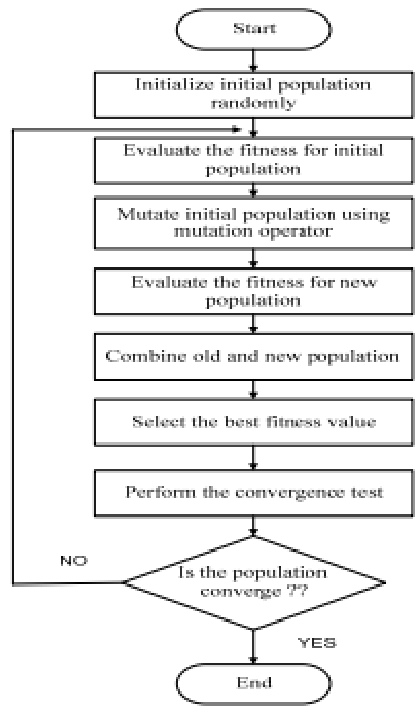

Figure 1: Flowchart of EP

3. RESULT AND DISCUSSION

The study was conducted on the 33-Bus Distribution System. The focus of this objective is to minimize the voltage profile during the charging/discharging condition. Three location from the 33-Bus Distribution system are being experimented which is bus 25, bus 26 and bus 27. The injected power into the 33-Bus Distribution system which it will acts as additional load to the distribution system. The 1-bus in the system are the slack bus while the 2-bus is the generator bus. The random generated number that generated randomly by the MATLAB simulation software are will be injected power which it will injected in the load bus data. The voltage profile of the bus will be optimized from the charging/discharging condition.

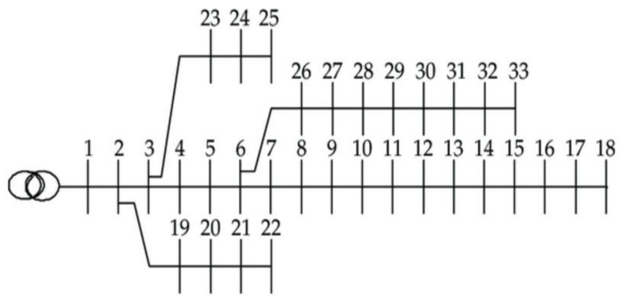

Figure 2: Single-Line Diagram of IEEE 33-Bus RDS

Table 3 tabulates the individuals for the initial population generated by the random generator. Apparently, the 20 individuals are the candidates generated by MATLAB representing the three control variables. The control variables are xP_3, xP_4, and xP_5. These values are the power demand by buses 25, 26 and 27 in the 33-Bus Distribution system. These power values represent the amount of power that will be injected to the charging system; which act at additional power supply to the system. These values are injection power, rather than the loading to the system. On the other hand, the inductive power will act as the load which become the additional load to the system. The three buses, i.e. buses 25, 26 and 27 are the arbitrary buses for the purpose of charging the system. Thus, the values are randomly generated by the random generator in MATLAB so that the proposed EP will eventually optimize these control variables so that the optimal solutions can ultimately be achieved.

Table 3: Initialization values for all the control variables, xP_3, xP_4 and xP_5

Individual	xP_3	xP_4	xP_5	V_{25}	V_{26}	V_{27}	V_{min}	V_{max}
1	0.921736	1.621986	0.710636	1.009282	1.010553	1.009513	0.965901	1.010553
2	1.939675	0.113162	1.918238	1.018684	1.019568	1.020637	0.97171	1.020637
3	0.042539	4.956911	0.799169	1.041421	1.046787	1.045937	0.985731	1.046787
4	3.101689	0.093475	1.037973	1.022138	1.021909	1.021451	0.973841	1.022138
5	0.552788	0.706349	1.602739	1.00402	1.005266	1.005793	0.962646	1.005793
6	2.549575	0.703352	1.238488	1.025431	1.026201	1.026092	0.975873	1.026201
7	2.205155	2.045629	0.889927	1.033607	1.035586	1.034882	0.980914	1.035586
8	0.410748	3.436134	1.100194	1.030979	1.034915	1.03457	0.979298	1.034915
9	3.458717	0.662903	1.407105	1.038507	1.039424	1.039605	0.983929	1.039605
10	3.206423	0.350595	2.451423	1.044327	1.046119	1.048063	0.987511	1.048063
11	1.595798	0.577229	1.492514	1.014714	1.01565	1.015981	0.969258	1.015981
12	3.001217	1.461956	1.100185	1.038915	1.040431	1.040089	0.984181	1.040431
13	1.980799	1.294815	1.963074	1.034774	1.03714	1.038269	0.981633	1.038269
14	3.733593	0.500431	0.738503	1.031573	1.031478	1.03051	0.979659	1.031573
15	2.150492	3.312916	0.177851	1.039793	1.042432	1.040519	0.984723	1.042432
16	4.135796	0.318384	1.080487	1.038611	1.038712	1.038336	0.983993	1.038712
17	3.434893	0.241668	1.713935	1.036778	1.037556	1.03826	0.982865	1.03826
18	1.593467	1.391851	2.833327	1.041807	1.045319	1.047909	0.985966	1.047909
19	1.763062	1.781518	1.980525	1.038297	1.041267	1.042422	0.983804	1.042422
20	1.703466	0.160746	1.654138	1.012783	1.013403	1.014017	0.968065	1.014017

Subsequently,

Table **4** tabulates the results for the optimal solutions for all the control variables, i.e. xP3, xP4, and xP5. From the table, it is explicitly indicated that all the values of all the control variables are similar, which has the difference between the maximum and minimum fitness much less than 0.00001 as the criterion for the stopping criterion. Only one value will be the optimal solution for xP_3, xP_4, and xP_5. From the table, the values for xP_3, xP_4, and xP_5 are 3.206423 MW, 0.350595 MW and 2.451423 MW respectively. The optimal minimum voltage is 0.987511 p.u., while the maximum optimal voltage in the whole system is 1.048063 p.u.. The voltage at all the three control buses can be referred to the same table, i.e.

Table **4**. These results imply that various random values for the control variables can reach an optimal solution as presented in

Table **4**. The developed EP optimization engine can be further utilized in solving other problems.

Table 4: Optimal solution for all the control variables, xP_3, xP_4 and xP_5

Individual	xP_3	xP_4	xP_5	V_{25}	V_{26}	V_{27}	V_{min}	V_{max}
1	3.206423	0.350595	2.451423	1.044327	1.046119	1.048063	0.987511	1.048063
2	3.206402	0.350574	2.451402	1.044326	1.046118	1.048063	0.987511	1.048063
3	3.206382	0.350554	2.451382	1.044325	1.046117	1.048062	0.98751	1.048062
4	3.206382	0.350554	2.451382	1.044325	1.046117	1.048062	0.98751	1.048062
5	3.20637	0.350542	2.45137	1.044325	1.046117	1.048061	0.98751	1.048061
6	3.206368	0.35054	2.451369	1.044325	1.046117	1.048061	0.98751	1.048061
7	3.20636	0.350533	2.451361	1.044324	1.046116	1.048061	0.98751	1.048061
8	3.20636	0.350532	2.451361	1.044324	1.046116	1.048061	0.98751	1.048061
9	3.206348	0.35052	2.451349	1.044324	1.046116	1.04806	0.98751	1.04806
10	3.206347	0.350519	2.451348	1.044324	1.046116	1.04806	0.98751	1.04806
11	3.20634	0.350512	2.451341	1.044324	1.046116	1.04806	0.987509	1.04806
12	3.206328	0.3505	2.451328	1.044323	1.046115	1.04806	0.987509	1.04806
13	3.206327	0.3505	2.451328	1.044323	1.046115	1.04806	0.987509	1.04806
14	3.206327	0.350499	2.451327	1.044323	1.046115	1.04806	0.987509	1.04806
15	3.206326	0.350498	2.451327	1.044323	1.046115	1.04806	0.987509	1.04806
16	3.206319	0.350491	2.451319	1.044323	1.046115	1.048059	0.987509	1.048059
17	3.206315	0.350487	2.451315	1.044323	1.046115	1.048059	0.987509	1.048059
18	3.206307	0.350479	2.451307	1.044322	1.046114	1.048059	0.987509	1.048059
19	3.206306	0.350478	2.451306	1.044322	1.046114	1.048059	0.987509	1.048059
20	3.206305	0.350477	2.451306	1.044322	1.046114	1.048059	0.987509	1.048059

4. CONCLUSION

This paper has presented evolutionary programming-based technique for plug-in-hybrid electric vehicle charging system. The proposed technique has been validated on 33-Bus Distribution system which three location are being validated. The results obtained from

Table **4** has validated the maximum and minimum voltage has achieved the voltage constraint of the distribution system which is 0.95<Vm<1.05 p.u. The developed EP optimization engine can be further utilized in solving other problems.

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