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Impact Evaluation of Different Plug-In Electric Vehicles Emission Using Precise Pricing Scheme

S.Suganya[1], T.Eswaran[2]
Department of Electrical and Electronics Engineering,
[1]AAA College of Engineering and Technology, Amathur, Virudhunagar, Tamilnadu, India.
[2]T.S.M. Jain college of Technology, Melur, Kallakurichi, Tamilnadu, India

Abstract:-The alarming rate of increasing automotive emission and green house gas has made the condition more critical. Without reducing the commercial and personal user functionalities, it is necessary to manage the tail pipe emission. Plug in hybrid electric vehicle (PHEV) has recently gained lot of interest with its emission reduction targets. Meanwhile, in order to meet the requirements of increased power due to PHEV charging, the distribution system should be reinforced. Thus, the charging station should be placed at appropriate location to scale down the operational cost. This paper proposes an agent-based simulation framework that considers both the optimal location and optimal control strategies for PHEV charge scheduling. A novel Two Phase Particle Swarm Optimization (TP-PSO) is proposed to solve the objective function. For the first time, different vehicle models are considered to generate solutions. The test result support the efficacy the proposed optimization method. Also, the economic and stability aspect of the system is addressed under various scenarios and several important findings are revealed.

Keywords*: Distribution system, Two phase Particle Swarm Optimization, Electric Vehicle models, Parameter assessment*

1. Introduction

Plug-in hybrid electric vehicles (PHEVs) are gaining much attention as a cleaner alternative vehicle. The economic viability of PHEVs, such as Chevrolet Volt, Ford C-Max, Nissan leaf, Toyota and Honda are likely to pave way for smart grid in near future [1, 2]. Along with the growing PHEV usage, the adverse impact of integrating it needs to be resolved. Uncontrolled charging may result in many power system problems such as power loss, over loading, etc. However, the proven benefits of PHEV with optimal charge and discharge scheduling cannot be neglected.

Several researches focus on investigating the application of electric vehicles and demand response implementations [3-6]. Results indicate that demand response programs with home appliances and electric vehicles decrease the operational cost of the system. To coordinate the charging of PHEVs a stochastic programming model is proposed in [7]to minimize the charging cost. Maximizing the operation profit while maintaining the service quality of the charging station, an online learning coupled with rule based decision making is addressed by Nian Liu et al. [8] based on time-of- use pricing.Numerous articles present studies considering PHEV with Vehicle-to-Grid (V2G) capability. Paper [9] discusses the economic aspect of using V2G strategy. The report concludes that without substantial investment,the EV charging can be added to demand side management. Battistelli et al. give a practical methodology to integrate V2G in a small distribution network and discussed the need of the aggregation model [10]. This paper intends to contribute to the establishment of this broader methodology as follows:

1. A three-area distribution system is presented for locating the smart charging station, while conserving the convenience of the aggregator and vehicle owner with five different vehicle models.

2. A new algorithm is proposed for achieving optimal solutions in less iteration.

3. Assessing each vehicle models impact on system parameters

4. Accordingly, to clarify the mobility pattern, scenarios close to real world is considered in this study.

2. Distribution System Framework

In this paper, the distribution system is sectioned into three areas each following a different mobility pattern [11-14]. The aggregator will optimally schedule the charging and discharging process of each area depending upon the electricity price and the vehicle availability. The sectionalized areas are detailed as follows:

A. A1: Home charging

The areas are classified based on the arrival and departure time of the vehicles. The vehicle owners of area 1 are considered to follow, home charging pattern, were the vehicleswill arrive to the parking garage only in the evening (at 18th hour) and departure is by morning (at 5th hour).

B. A2: Work Station charging

In area 2, the vehicles will follow morning arrival (at 9th hour) and evening departure (at 17th hour). This charging pattern is closely related to the real time working people's preference and it corresponds to parking garages located in the commercial and business areas.

C. A3: Mixed Charging

This charging pattern combines the home and workstation charging[15-17]. The parking garage corresponds to home charging during night and workstation charging during day. The peak and off-peak hour, the arrival and the departure time are illustrated in Table I.

Table I: System Information and vehicle availability

Area	VehicleAvailability(Hour)		Peakhour	Off-Peakhour
	ArrivalTime	DepartureTime		
A1	18	6	18-22	1-6,23,24
A2	9	17	9-12	13-17
A3	Anytime		9-12, 18-22	1-6,13-17,23,24

3. Proposed Methodology

The parking garage may not have the same type of vehicles parked. Thus, analyzing the impact of different vehicle models in charging and emission mode cannot beneglected. In this aspect, five different electric vehicle models considering its configuration in both charge sustaining and charge depleting mode is incorporated in this study.

A group of work has been dedicated to aggregator such as optimal placement of charging station and scheduling of vehicles in the parking lot by considering the system parameters and satisfying the objective. The proposed scheduling methodology with different vehicle models and the role of aggregator is depicted in Figure 1. The vehicle owners with different vehicle models will submit their information about their arrival and departure time to the aggregator who will optimally schedule the vehicles in each area. Vehicle to grid strategy is also permitted during the peak price periods to reduce the operational cost.

4. Proposed Metaheuristic Solving tool

The proposed algorithm consists of two phases namely, multi-evolutionary phase and single-evolutionary phase. In multi-evolutionary phase, initially random clusters are generated in way that it uniformly covers the decision space. Each cluster is allowed evolve independently in the search space and are set to maintain its own particle-best (p_{best}) and cluster-best (c_{best}). The later term represents the best particle in a cluster based on the complete history of evolution.

Algorithm 1 - Multi evolutionary phase

1: Input random generate M number of independent cluster

2: M=1; $iter$=1

3: Repeat

4: For each par= 1…….N do

5: Update the velocity and position of each particle based on (10) and (11).

6: End for

i. Evaluate the fitness of the particle.

ii. Determine the particle-best of each cluster

7: Determine the cluster-best of each individual group 8: M=M+1

9: Execute Algorithm 2 - Single evolutionary phase

10: $iter = iter + 1$

11: *Output fitness function and stop*

Algorithm 2 – Single evolutionary phase

1: Input cluster best c_{best}

2: Repeat for each individual group

3: Compute local-best (l_{best})

4: With l_{best}as reference

5: Update the velocity and position of the particle

6: Output global best $g_{best}$and stop

The modified PSO demonstrates better performance on test system as detailed in section 5. The attractive featureis that the proposed meta-heuristic tool maintains the simplicity of existing PSO without adding any new parameter to improve its convergence.

5. Results and Discussion

The performance of the proposed system is tested in IEEE 69-bus distribution system. IEEE 69-bus radial distribution system is connected through 12.66kV distribution system with total of 3801.89kW real power load and 2694.1kVAr reactive power load. The real and reactive power supplied from substation is 4026.85kW and 2796.25kVAr respectively.The optimal location of charging station in each area is evaluated using the optimization tool. Location 2, 48 and 15 are identified as suitable location in area 1, 2 and 3 respectively.

The proposed objective deals with identifying the optimal location by considering technical challenges and validating its performance under two scenarios namely;

Scenario 1: Charging only

Scenario 2: Both charging and discharging

A. Power loss assessment

The power loss is evaluated with the charging stations at optimal location 2, 48 and 15 for both scenarios. The performance of the system in power loss perspective is shown in Table II.

Table II: Performance in Power Loss Perspective

Area	Optimal Location of Charging station	Power Loss (KW)	
		Scenario 1	Scenario 2
Area 1	2	224.9545	224.9538
Area 2	48	225.0526	225.0215
Area 3	15	231.6690	229.5762

In scenario 2, the loss is reduced from 224.9545 to 224.9538 for A1. Similarly, A2 and A3 also have loss reduction to a considerable extend. This shows that the discharging of power adopted in scenario 2 is capable of reducing the system load resulting in loss reduction. Also A1 is having less additional load because of more Nıssan leaf model, compared to other two areas which result in reduced system loss.

B. PHEV scheduling

After finding the suitable location with power loss considerarion, the vehicles in each area need to be optimally scheduled. The Time-of- Use (ToU) pricing scheme is utilized for scheduling the vehicles. The 24 hour vehicle scheduling is depicted in Figure 3(a), 3(b) and 3(c) for A1, A2 and A3 areas respectively.In case of home charging, the electricity price is less for most of the hours, as a result the operational cost is found to be 2.5502 $/day. However, the workstation charging is accompanied by high electricity price for longer period. As it is a day time scheduling, its operational cost is 9.4555 $/day. It is inferred that the operational cost is less in night time schedling with more off-peak hours. By using mixed charging, the operational cost is 5.1554 $/day which is an intermediate one.

C. Load reduction assessment

Based on the classification and manufacturer, each vehicle model is considered have distinct fuel consumption, electricity consumption as shown in Table III.

Table III: Technical parameters of each vehicle model in charge sustaining mode

Model Name	Fuel Type **(Engine)**	Fuel Consumption **(L/100km)**		Electricity Consumption **(kWh/km)**	
		City	Highway	City	Highway
CHEVROLET Volt	Gasoline	6.71	5.87	0.207	0.225
FORD C-Max Plug-in Hybrid	Gasoline	5.34	5.73	0.194	0.228
NISSAN Leaf	NA	0.00	0.00	0.161	0.205
TOYOTA Prius Plug-in	Gasoline	4.61	4.79	0.180	0.180
HONDA Fit EV	NA	0.00	0.00	0.169	0.209
Conventional					
VOLKSWAGEN Beetle	Diesel	8.20	6.04	NA	NA
VOLVO C70 FWD	Gasoline	12.57	8.46	NA	NA

Obviously, the additional load depends on the electricity consumption by the vehicular model. The additional load is calculated as 87.8 kW, 89.4 kW and 91.45 kW in A1, A2 and A3 areas respectively. From this it can be observed that, though each area comprises of same vehicle model, its proportion in the parking fleet brings variation in the needed load. Nıssan leaf vehicle models have electricity consumption of 0.161 kWh/km, as A1 consist 30 number such vehicles its additional load is less. With scenario 2, the additional load gets reduced. The load reduction in each parking fleet is shown in Figure I.

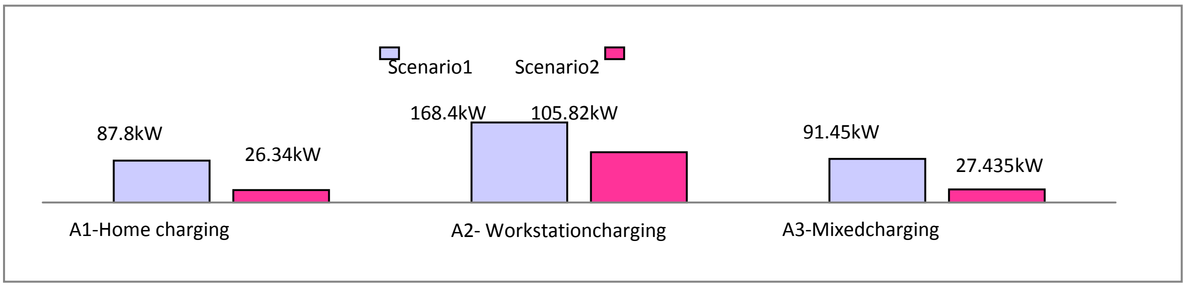

Figure I. Additional load in the charging station

A. Emission assessment

The emission of each parking fleet is evalauted and the results are shown in Table IV, V and VI for the fleet in A1, A2 and A3 respectively.

Table IV: Performance in Power Loss Perspective

Emission Sources	Total fleet (tones CO2- eq. /day)	Per vehicle (kg CO2-eq./day)	Per km (g CO2-eq./km)
Electricity	0.16	1.64	34.1
Fuel	0.02	0.23	4.8
Total	0.19	1.87	38.9
Conventionalvehicle	1.31	13.10	272.9

Table V: Emission of the parking fleet in A2

Emission Sources	Total fleet (tones CO2-eq. /day)	Per vehicle (kg CO2-eq./day)	Per km (g CO2-eq./km)
Electricity	0.15	1.50	31.3
Fuel	0.07	0.69	14.4
Total	0.22	2.19	45.7
Conventional vehicle	1.31	13.10	272.9

Table VI: Emission of the parking fleet in A3

Emission Sources	Total fleet	Per vehicle	Per km

	(tones CO2- eq./day)	(kg CO2-eq./day)	(g CO2-eq./km)
Electricity	0.15	1.54	32.1
Fuel	0.05	0.46	9.6
Total	0.20	2.00	41.6
Conventionalvehicle	1.31	13.10	272.9

For comparing the emission function of electric and combustion engine vehicles, two conventional vehicles such as Volkswagen Beetle and Volvo C70 FWD (S5, 2.5L) as shown in Table 6 are considered. From the result, it is inferred that A2 is having an emission of 0.22 (tones CO2- eq. /day) which is reduced to 0.20 (tones CO2- eq. /day) in A3. Further reduction in emission is observed in A1 with 0.19 (tones CO2- eq. /day). Among the total of 100 Electric vehicles, A1 is having 50 zero fuel consumption vehicles (30 Nissan leaf vehicles and 20 Honda Fit EVs), as a result the emission is less in that area.

6. Conclusion

In PHEV charging stations, the model and configuration of one vehicle differ from the other. In this conceptual basis, a three-area distribution system is analyzed with five different vehicle models in this paper. Each area is set to follow a different mobility pattern. To control the peak load, a smart charging scheme needs to be implemented according to the technical limitations. For which, a TP-PSO algorithm is introduced, it is found that the location nearer to the substation i.e. location 2 is found to be capable of reducing the system issues to a considerable extend. Among different vehicle models, Nissan leaf type of electric vehicle is realistic enough to reach valuable conclusions with its less electricity and zero fuel consumption configuration.

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