Hybrid Swarm Intelligence-Based Optimization for Charging Plug-in Hybrid Electric Vehicle

Imran Rahman[1(✉)], Pandian Vasant[1], Balbir Singh Mahinder Singh[1], and M. Abdullah-Al-Wadud[2]

[1] Department of Fundamental and Applied Sciences, Universiti Teknologi PETRONAS, Tronoh, Malaysia
{imran.iutoic,pvasant}@gmail.com, balbir@petronas.com.my
[2] Department of Software Engineering, College of Computer and Information Sciences, King Saud University, Riyadh, KSA
mwadud@ksu.edu.sa

Abstract. Plug-in hybrid electric vehicle (PHEV) has the potential to facilitate the energy and environmental aspects of personal transportation, but face a hurdle of access to charging system. The charging infrastructure has its own complexities when it is compared with petrol stations because of the involvement of the different charging alternatives. As a result, the topic related to optimization of Plug-in hybrid electric vehicle charging infrastructure has attracted the attention of researchers from different communities in the past few years. Recently introduced smart grid technology has brought new challenges and opportunities for the development of electric vehicle charging facilities. This paper presents Hybrid particle swarm optimization Gravitational Search Algorithm (PSOGSA)-based approach for state-of-charge (SoC) maximization of plug-in hybrid electric vehicles hence optimize the overall smart charging.

Keywords: Smart charging · State-of-charge · Plug-in hybrid electric vehicle · PSOGSA · Swarm intelligence

1 Introduction

The vehicular network recently accounts for around 25% of CO_2 emissions and over 55% of oil consumption around the world [1]. Carbon dioxide is the primary greenhouse gas emitted through human activities like combustion of fossil fuels (coal, natural gas, and oil) for energy and transportation. Several researchers have proved that a great amount of reductions in greenhouse gas emissions and the increasing dependence on oil could be accomplished by electrification of transport sector [2]. Indeed, the adoption of hybrid electric vehicles (HEVs) has brought significant market success over the past decade. Vehicles can be classified into three groups: internal combustion engine vehicles (ICEV), hybrid electric vehicles (HEV) and all- electric vehicles (AEV) [3]. Plug-in hybrid electric vehicles (PHEVs) which is very recently introduced promise to boost up the overall fuel efficiency by holding a higher capacity battery system, which can be directly charged from traditional power grid system,

N.T. Nguyen et al. (Eds.): ACIIDS 2015, Part II, LNAI 9012, pp. 22–30, 2015.
DOI: 10.1007/978-3-319-15705-4_3

that helps the vehicles to operate continuously in “all-electric-range" (AER) All-electric vehicles or AEV is a vehicle using electric power as only sources to move the vehicle [4]. Plug-in hybrid electric vehicles with a connection to the smart grid can possess all of these strategies. Hence, the widely extended adoption of PHEVs might play a significant role in the alternative energy integration into traditional grid systems [5]. There is a need of efficient mechanisms and algorithms for smart grid technologies in order to solve highly heterogeneous problems like energy management, cost reduction, efficient charging infrastructure etc. with different objectives and system constraints [6].

According to a statistics of Electric Power Research Institute (EPRI), about 62% of the entire United States (US) vehicle will comprise of PHEVs within the year 2050 [7]. Large numbers of PHEVs have the capability to threaten the stability of the power system. For example, in order to avoid interruption when several thousand PHEVs are introduced into the system over a short period of time, the load on the power grid will need to be managed very carefully. One of the main targets is to facilitate the proper interaction between the power grid and the PHEV. For the maximization of customer satisfaction and minimization of burdens on the grid, a complicated control mechanism will need to be addressed in order to govern multiple battery loads from a numbers of PHEVs appropriately [8]. The total demand pattern will also have an important impact on the electricity industry due to differences in the needs of the PHEVs parked in the deck at certain time [9]. Proper management can ensure strain minimization of the grid and enhance the transmission and generation of electric power supply. The control of PHEV charging depending on the locations can be classified into two groups; household charging and public charging. The proposed optimization focuses on the public charging station for plug-in vehicles because most of PHEV charging is expected to take place in public charging locations [10].

Charging stations are needed to be built at workplaces, markets/shopping malls and home. In [11], authors proposed the necessity of building new smart charging station with effective communication among utilities along with sub-station control infrastructure in view of grid stability and proper energy utilization. Furthermore, assortment of charging stations with respect to charging characteristics of different PHEVs traffic mobility characteristics, sizeable energy storage, cost minimization; Quality of Services (QoS) and optimal power of intelligent charging station are underway [12].

One of the important constraints for accurate charging is State-of-Charge (SoC). Charging algorithm can accurately be managed by the precise State of charge estimation. The performance of PHEV depends upon proper utilization of electric power which is solely affected by the battery state-of-charge (SoC). In Plug-in hybrid electric vehicles (PHEVs), a key parameter is the state-of-charge (SoC) of the battery as it is a measure of the amount of electrical energy stored in it. It is analogous to fuel gauge on a conventional internal combustion (IC) car [13]. There is a need of in-depth study on maximization of average SoC in order to facilitate intelligent energy allocation for PHEVs in a charging station. Hybrid PSOGSA was developed by Seyedali Mirjalili [14] at soft computing research lab of Universiti Teknologi Malaysia (UTM) in 2010 in order to integrate the ability of exploitation in PSO with the ability of exploration in GSA.

PSOGSA-based optimization has already been used by the researchers for economic load dispatch [15], optimal static state estimation [16], dual channel speech enhancement [17], training feed-forward neural networks [18] and multi-distributed generation planning [19]. Specifically, we are investigating the use of the Hybrid particle swarm optimization Gravitational Search Algorithm (PSOGSA) method for developing real-time and large-scale optimizations for allocating power.

The remainder of this paper is organized as follows: Next section will describe the specific problem that we are trying to solve. We will provide the optimization objective and constraints, flowchart of PSOGSA algorithm as well as describe how the algorithm works for our optimization problems. The simulation results and analysis are presented then with an extensive analysis. Finally, conclusions and future directions are drawn.

2 Problem Formulation

The idea behind smart charging is to charge the vehicle when it is most beneficial, which could be when electricity price, demand is lowest, when there is excess capacity [20].

Suppose, there is a charging station with the capacity of total power P. Total N numbers of PHEVs need to serve in a day (24 hours). The proposed system should allow PHEVs to leave the charging station before their expected leaving time for making the system more effective. It is worth to mention that, each PHEV is regarded to be plugged-in to the charging station once. The main aim is to allocate power intelligently for each PHEV coming to the charging station. The State-of-Charge is the main parameter which needs to be maximized in order to allocate power effectively. For this, the objective function considered in this paper is the maximization of average SoC and thus allocate energy for PHEVs at the next time step. The constraints considered are: charging time, present SoC and price of the energy.

The objective function is defined as:

$$\max J(k) = \sum_i w_i(k) SoC_i(k+1) \tag{1}$$

$$w_i(k) = f\left(C_{r,i}(k), T_{r,i}(k), D_i(k)\right) \tag{2}$$

$$C_{r,i}(k) = \left(1 - SoC_i(k)\right) * C_i \tag{3}$$

where $C_{r,i}(k)$ is the battery capacity (remaining) needed to be filled for i no. of PHEV at time step k; C_i is the battery capacity (rated) of the i no. of PHEV; remaining time for charging a particular PHEV at time step k is expressed as $T_{r,i}(k)$; the price difference between the real-time energy price and the price that a specific customer at the i no. of PHEV charger is willing to pay at time step k is presented by $D_i(k)$; $w_i(k)$ is the charging weighting term of the i no. of PHEV at time step k

(a function of charging time, present SoC and price of the energy); $SoC_i(k+1)$is the state of charge of the i no. of PHEV at time step $k+1$.

Here, the weighting term indicates a bonus proportional to the attributes of a specific PHEV. For example, if a PHEV has a lower initial SoC and less charging time (remaining), but the driver is eager to pay a higher price, the system will provide more power to this particular PHEV battery charger:

$$w_i(k)\alpha\left[Cap_{r,i}(k)+D_i(k)+ {}^{1}\!/\!_{T_{r,i}}(k)\right] \tag{4}$$

The charging current is also assumed to be constant overΔt.

$$\left[SoC_i(k+1)-SoC_i(k)\right].Cap_i=Q_i=I_i(k)\Delta t \tag{5}$$

$$SoC_i(k+1)=SoC_i(k)+I_i(k)\Delta t/Cap_i \tag{6}$$

Where the sample timeΔt is defined by the charging station operators, and $I_i(k)$ is the charging current overΔt.

The battery model is regarded as a capacitor circuit, where C_i is the capacitance of battery (Farad). The model is defined as:

$$C_i.\frac{dV_i}{dt}=I_i \tag{7}$$

Therefore, over a small time interval, one can assume the change of voltage to be linear,

$$C_i.\left[V_i(k+1)-V_i(k)\right]/\Delta t=I_i \tag{8}$$

$$V_i(k+1)-V_i(k)=I_i\Delta t/C_i \tag{9}$$

As the decision variable used here is the allocated power to the PHEVs, by replacing $I_i(k)$ with $P_i(k)$the objective function finally becomes:

$$J(k)=\sum w_i.\left[SoC_i(k)+\frac{2P_i(k)\Delta t}{0.5.C_i.\left[\sqrt{\frac{2P_i(k)\Delta t}{C_i}+V^2{}_i(k)}+V_i(k)\right]}\right] \tag{10}$$

Power obtained from the utility ($P_{utility}$) and the maximum power ($P_{i,max}$) absorbed by a specific PHEV are the primary energy constraints being considered in this paper.

The overall charging efficiency of a particular charging infrastructure is described by η. From the system point of view, charging efficiency is supposed to be constant at any given time step. Maximum battery SoC limit for the i no. of PHEV is $SoC_{i,max}$. When SoC_i reaches the values close to $SoC_{i,max}$, the i no. of battery charger shifts to a standby mode. The state of charge ramp rate is confined within limits by the constraint ΔSoC_{max}. The overall control system is changed the state when i) system utility data updates; ii) a new PHEV is plugged-in; iii) time period Δt has periodically passed.

3 The Hybrid PSOGSA Algorithm

In this paper, a new hybrid population-based algorithm (PSOGSA) [14] is proposed with the combination of Particle Swarm Optimization (PSO) and Gravitational Search Algorithm (GSA). The basic idea is to fit in the exploitation ability in PSO with the

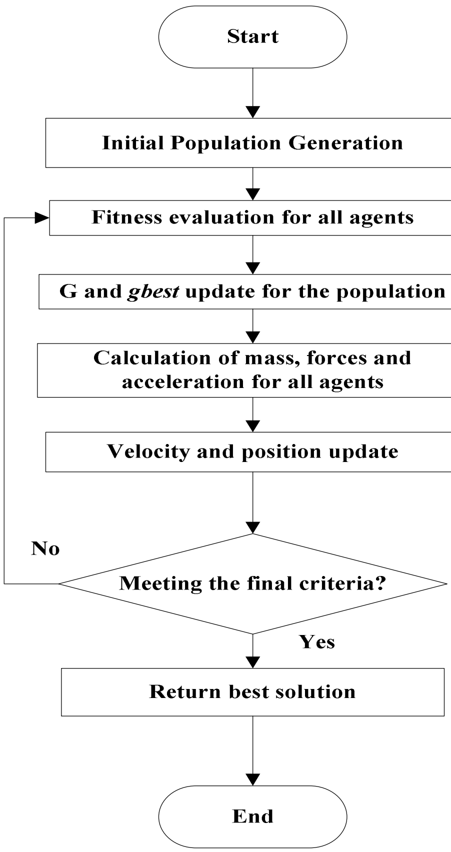

Fig. 1. Hybrid PSOGSA Algorithm Flowchart

exploration ability in GSA to synthesize both algorithms' strength. The basic idea of PSOGSA is to combine the ability of social thinking (*gbest*) in PSO with the local search capability of GSA. In order to combine these two algorithms, velocity update is proposed as

$$v_i(t+1) = w \times v_i(t) + \alpha' \times rand \times ac_i(t) + \beta' \times rand \times (gbest - x_i(t)) \quad (11)$$

where $v_i(t)$is the velocity of agent i at iteration t, w is a weighting factor, *rand* is a random number between 0 and 1, $ac_i(t)$ is the acceleration of agent at iteration t, and *gbest* is the best solution so far. The position of the particle $x_i(t+1)$ in each iteration is updated using the equation

$$x_i(t+1) = x_i(t) + v_i(t+1) \quad (12)$$

The flowchart of hybrid PSOGSA method is shown in fig 1.

4 Simulation Results and Analysis

The Hybrid PSOGSA algorithm were applied to find out best fitness of the objective function. All the simulations were run on a Core™ i5-3470M CPU@ 3.20 GHz processor, 4.00 GB RAM and MATLAB R2013a.

The parameter settings for Hybrid PSOGSA are demonstrated in Table 1. The size of swarm is set to the standard value which is 100 and values for C1 and C2 were taken as 0.5 and 1.5 [21]. Other parameters are set from the experiences of previous research articles [22, 23, 24].

Table 1. PSOGSA parameter settings

Parameters	Values
Size of the swarm	100
Maximum Iteration	100
PSO parameter, C_1	0.5
PSO parameter, C_2	1.5
Gravitational Constant, G_0	1
GSA Constant parameter, α	23
Number of runs	20

Table 2 summarizes the simulation results for 50 and 100 plug-in hybrid electric vehicles (PHEVs) respectively for finding the maximum fitness value of objective function J (k). In order to evaluate the performance and show the efficiency and superiority of the proposed algorithm, we ran each scenario total 20 times.

Table 2. Average best fitness and Computational time for PSOGSA

Number of PHEVs	Average Best Fitness	Average Computational Time
50	144.838	4.248 Sec.
100	183.094	7.877 Sec.

The average best fitness increases when number of vehicles are more in number from 144.838 to 183.094. Moreover, the computational time increases for 100 PHEVs. The average computational time for 50 PHEVs is 4.248 seconds while for 100 PHEVs, it becomes 7.877. Computational complexity of hybrid algorithm can be controlled by rigorous attempts of parameter tuning which will be our further research concern.

Fig. 2 and Fig. 3 shows the convergence behavior (iteration vs. Best fitness) for both 50 and 100 numbers of PHEVs. From the figures, it is clear that, the convergence occurs at the same pattern hence prove the stability of this hybrid optimization. It can be apparently seen that although the algorithm has been set to run for maximum 100 iterations, the fitness value converges before 10 iterations and become stable. So, there is an early convergence which may cause the fitness function to trap into local minima. This can be avoided by increasing the size of swarm hence the computational time will also be increased as well. As a result, a trade-off should be taken into consideration between the proper convergence and computational time.

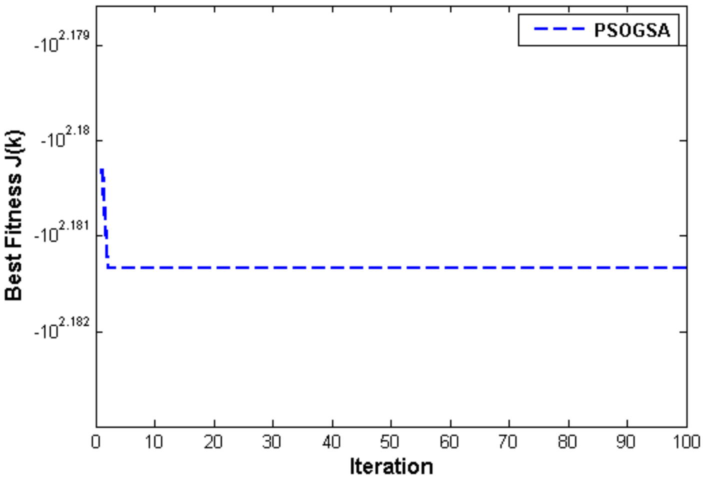

Fig. 2. Best Fitness vs. Iteration (50 PHEVs)

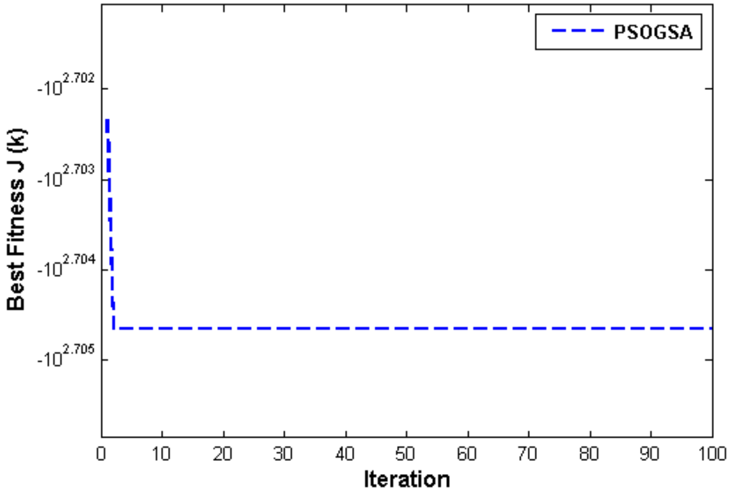

Fig. 3. Best Fitness vs. Iteration (100 PHEVs)

5 Conclusion and Future Works

In this paper, Hybrid particle swarm optimization Gravitational Search Algorithm (PSOGSA)-based optimization was performed in order to optimally allocate power to each of the PHEVs entering into the charging station. A sophisticated controller will need to be designed in order to allocate power to PHEVs appropriately. For this wake, the applied algorithm in this paper is a step towards real-life implementation of such controller for PHEV Charging Infrastructures. Here, two (02) different numbers of PHEVs were considered for MATLAB Simulation. The researchers should try to develop efficient control mechanism for charging infrastructure in order to facilitate upcoming PHEVs penetration in highways. In future, more vehicles should be considered for intelligent power allocation strategy as well as should be applied to ensure higher fitness value and low computational time.

Acknowledgement. The authors would like to thank Universiti Teknologi PETRONAS (UTP) for supporting the research under UTP Graduate Assistantship (GA) scheme.

References

1. Transport, Energy and C02-Moving Towards Sustainability, Paris (2009). http://www.iea.org/newsroomandevents/pressreleases/2009/october/name,20274,en.html
2. Holtz-Eakin, D., Selden, T.M.: Stoking the fires? CO2 emissions and economic growth. Journal of public economics **57**(1), 85–101 (1995)
3. Tie, S.F., Tan, C.W.: A review of energy sources and energy management system in electric vehicles. Renewable and Sustainable Energy Reviews **20**, 82–102 (2013)
4. Environmental assessment of plug-in hybrid electric vehicles. Volume 1: Nationwide greenhouse gas emissions, Electric Power Research. Institute (EPRI), Palo Alto, CA, Tech. Rep. 1015325 (2007)

5. Lund, H., Kempton, W.: Integration of renewable energy into the transport and electricity sectors through V2G. Energy policy **36**, 3578–3587 (2008)
6. Hota, A.R., Juvvanapudi, M., Bajpai, P.: Issues and solution approaches in PHEV integration to the smart grid. Renewable and Sustainable Energy Reviews **30**, 217–229 (2014)
7. Soares, J., Sousa, T., Morais, H., Vale, Z., Canizes, B., Silva, A.: Application-Specific Modified Particle Swarm Optimization for energy resource scheduling considering vehicle-to-grid. Applied Soft Computing **13**(11), 4264–4280 (2013)
8. Su, W., Chow, M.-Y.: Computational intelligence-based energy management for a large-scale PHEV/PEV enabled municipal parking deck. Applied Energy **96**, 171–182 (2012)
9. Su, W., Chow, M.-Y.: Performance evaluation of a PHEV parking station using particle swarm optimization. In: 2011 IEEE Power and Energy Society General Meeting, pp. 1-6 (2011)
10. Su, W., Chow, M.-Y.: Performance evaluation of an EDA-based large-scale plug-in hybrid electric vehicle charging algorithm. IEEE Transactions on Smart Grid **3**, 308–315 (2012)
11. Boyle, G.: Renewable Electricity and the Grid: The Challenge of Variability. Earth scan Publications Ltd (2007)
12. Hess, A., Francesco, M., Reinhardt, M., Casetti, C.: Optimal deployment of charging stations for electric vehicular networks. In: Proceedings of the First Workshop on Urban Networking, pp. 1-6. ACM, New York (2012)
13. Chang, W.-Y.: The State of Charge Estimating Methods for Battery: A Review. ISRN Applied Mathematics, **2013**, Article ID 953792 (2013)
14. Mirjalili, S., Hashim, S.Z.M.: A new hybrid PSOGSA algorithm for function optimization. In: IEEE International Conference on Computer and Information Application (ICCIA), pp. 374-377 (2010)
15. Dubey, H.M., Pandit, M., Panigrahi, B., Udgir, M.: Economic Load Dispatch by Hybrid Swarm Intelligence Based Gravitational Search Algorithm. International Journal of Intelligent Systems & Applications **5** (2013)
16. Mallick, S., Ghoshal, S.P., Acharjee, P., Thakur, S.S.: Optimal static state estimation using improved particle swarm optimization and gravitational search algorithm. International Journal of Electrical Power & Energy Systems **52**, 254–265 (2013)
17. Kunche, P., Rao, G.S.B., Reddy, K.V.V.S., Maheswari, R.U.: A new approach to dual channel speech enhancement based on hybrid PSOGSA. International Journal of Speech Technology 1-12 (2014)
18. Mirjalili, S., Mohd Hashim, S.Z., Moradian Sardroudi, H.: Training feedforward neural networks using hybrid particle swarm optimization and gravitational search algorithm. Applied Mathematics and Computation **218**, 11125–11137 (2012)
19. Tan, W.S., Hassan, M.Y., Rahman, H.A., Abdullah, M.P., Hussin, F.: Multi-distributed generation planning using hybrid particle swarm optimisation-gravitational search algorithm including voltage rise issue. IET Generation, Transmission & Distribution **7**, 929–942 (2013)
20. Mayfield, D.: Site Design for Electric Vehicle Charging Stations, ver.1.0, Sustainable Transportation Strategies (2012)
21. Ganesan, T., Vasant, P., Elamvazuthy, I.: A hybrid PSO approach for solving non-convex optimization problems. Archives of Control Sciences **22**(1), 87–105 (2012)
22. Ganesan, T., Elamvazuthi, I., Ku Shaari, K.Z., Vasant, P.: Swarm intelligence and gravitational search algorithm for multi-objective optimization of synthesis gas production. Applied Energy **103**, 368–374 (2013)
23. Vasant, P.: Hybrid Evolutionary Optimization Algorithms: A Case Study in Manufacturing Industry. Smart Manufacturing Innovation and Transformation: Interconnection and Intelligence **59** (2014)
24. Rahman, I., Vasant, P.M., Singh, B.S.M., Abdullah-Al-Wadud, M.: Intelligent energy allocation strategy for PHEV charging station using gravitational search algorithm. AIP Conference Proceedings **1621**, 52–59 (2014)