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ORIGINAL ARTICLE

On the performance of accelerated particle swarm optimization for charging plug-in hybrid electric vehicles

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Abstract Transportation electrification has undergone major changes since the last decade. Success of smart grid with renewable energy integration solely depends upon the large-scale penetration of plug-in hybrid electric vehicles (PHEVs) for a sustainable and carbon-free transportation sector. One of the key performance indicators in hybrid electric vehicle is the State-of-Charge (SoC) which needs to be optimized for the betterment of charging infrastructure using stochastic computational methods. In this paper, a newly emerged Accelerated particle swarm optimization (APSO) technique was applied and compared with standard particle swarm optimization (PSO) considering charging time and battery capacity. Simulation results obtained for maximizing the highly nonlinear objective function indicate that APSO achieves some improvements in terms of best fitness and computation time.

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 such as 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]. Certainly, 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]. Recently introduced plug-in hybrid electric vehicles (PHEVs) have the potential to increase the total fuel efficiency because of a large size on board battery charged directly from the traditional

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Nomenclature

PHEVs	plug-in hybrid electric vehicles
EPRI	electric power research institute
V2G	vehicle-to-grid
SoC	State-of-Charge
ICEV	internal combustion engine vehicles
AEVs	all-electric vehicles
HEVs	hybrid electric vehicles
AER	all-electric-range
$I_i(k)$	charging current over Δt
$C_{r,i}(k)$	remaining battery capacity required to be filled for i-th PHEV at time step k
C_i	rated battery capacity of the i-th PHEV (Farad)
$T_{r,i}(k)$	remaining time for charging the i-th PHEV at time step k
$D_i(k)$	price difference
$w_i(k)$	charging weighting term of the i-th PHEV at time step
$SoC_i(k+1)$	State-of-Charge of the i-th PHEV at time step $k+1$
$SoC_{i,\max}$	user-defined maximum battery SoC limit for the i-th PHEV
P_{utility}	power available from the utility
$P_{i,\max}$	maximum power that can be absorbed by a specific PHEV
η	overall charging efficiency of the charging station

electric grid, that supports the automobiles to function uninterruptedly in "All-Electric-Range" (AER). All-electric vehicles or AEV is a vehicle using electric power as only sources to move the vehicle [4]. PHEVs integrated with smart grid will possess all of recently introduced strategies. Hence, widely stretched acceptance of PHEVs should play an important role in the sustainable energy addition into existing power grid systems [5]. Effective mechanisms and systems for smart grid expertise are needed in order to solve very diverse complications such as energy management, cost reduction, and efficient charging infrastructure with different objectives and system constraints [6].

According to EPRI – Electric Power Research Institute, almost 62% of entire United States (US) transport will comprise of PHEVs within the year 2050 [7]. Large numbers of PHEVs have the capability to make threats to the stability of the power system. For example, in order to avoid disturbance when several thousand PHEVs are introduced into the system over a small 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 communication between the power grid and the PHEV. For the maximization of customer contentment and minimization of burdens on the grid, a complicated control appliance will need to be addressed in order to govern multiple battery loads from a numbers of PHEVs properly [8]. The overall demand arrangement will have a significant impact on the power production due to variances in the requirements of the electric vehicles parked in the parking deck at a specific 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].

Widespread penetration of electric vehicles in the vehicular market is influenced by the systematized charging infrastructures. The power requirement from these new loads actually put extra burden on the existing power systems [12]. For this, some strategies have been proposed by the researchers [13,14] in order to facilitate the PHEV charging infrastructures. Charging infrastructures are required to be constructed at offices, marketplaces and near households. Authors [15] proposed the requirement of constructing innovative smart charging infrastructures with efficient communication networks among the utilities accompanied by well-equipped control infrastructures in order to achieve proper grid stability as well as proper utilization of energy. Moreover, adequate energy storage facilities, cost reduction, Quality of Services (QoS) and optimum power allocation to intelligent charging infrastructures are in progress [16]. As a result, development of dependable, effective, vigorous and cost-effective charging infrastructures is ongoing. Numerous techniques and approaches have proposed for placement of charging infrastructures for PHEVs [17].

State-of-Charge (SoC) is one of the significant constraints for precise charging [11]. A graph of a distinctive Lithium-ion cell voltage versus State-of-Charge is presented in Fig. 1. The figure indicates that the slope of the curve below 20% and above 90% is high enough to result in a significant voltage difference to be depended on by measurement circuits and charge balancing control. Accelerated PSO was developed by Yang [18] at Cambridge University in 2007 in order to accelerate the convergence of the algorithm that is to use the global best only. PSO and APSO-based optimizations have already been studied by the researchers for optimal design of substation grounding grid [19], non-convex optimization [20,21], per-

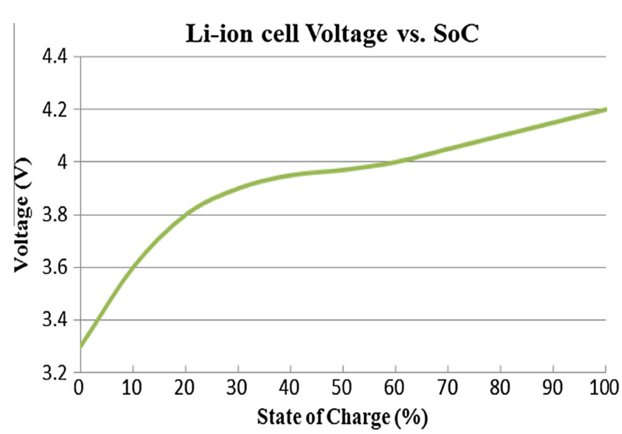

Figure 1 Voltage of Lithium-ion cell versus State-of-Charge [28].

formance analysis of MIMO radar waveform [22], design of frame structures [23], dual channel speech enhancement [25], synthesis gas production [26] and a faster path planner [27]. Specifically, we are investigating the use of the Accelerated particle swarm optimization (APSO) method for developing real-time and large-scale optimizations for allocating power.

The paper is structured as follows: Next section will define the particular optimization problem that is trying to be solved. Optimization fitness function and constraints, mathematical construction of proposed algorithm and assessment of the APSO technique explain how the particular algorithm solves our stated optimization problems. The experimental results and simulation analysis are presented then with a broad comparison with stand-alone PSO. Finally, conclusions and future research directions are drawn.

2. Problem statement

Smart charging of PHEV considers energy demand, price of energy and surplus capacity [6].

For creating the fitness function let us assume a charging infrastructure with P, total power capacity. Overall N quantities of PHEVs require to be served in whole day (24 h). The entire charging system should facilitate PHEVs to leave the charging infrastructure before the estimated leaving time for creating the structure more efficient. It is worth to mention that, each PHEV is regarded to be plugged-into 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 efficiently. For this, the fitness function considered in this paper is the maximization of average SoC and thus allocates energy for PHEVs at the next time step. Time of charging, present State-of-Charge (SoC) and energy price are the three constraints taken into account in this paper [8].

The fitness function is defined as follows:

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

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

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

where $C_{r,i}(k)$ is the battery capacity (r = remaining) needed to be filled for i no. of PHEV at time step k; C_i is the battery capacity (rated) of the 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 $k+1$.

Weighting term denotes a gratuity proportional to features of specific vehicles. For an example, if a PHEV has a lower preliminary SoC and less time for charging is remaining, but the driver is willing to give extra price, the charging system will allocate more power to that particular vehicle battery charger:

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

Moreover, charging current is assumed to be fixed over time period, Δt.

$$SoC_i(k+1) = SoC_i(k) + I_i(k)\Delta t / C_i \tag{5}$$

Δt = The sample is usually defined by the operators of charging station whereas the charging current is denoted as $I_i(k)$ over period Δt.

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

$$C_i \cdot \frac{dV_i}{dt} = I_i \tag{6}$$

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

$$V_i(k+1) - V_i(k) = I_i \Delta t / C_i \tag{7}$$

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

$$I_i(k) = P_i(k) / 0.5 \times [V_i(K+1) + V_i(k)] \tag{8}$$

Now, by substituting $I_i(k)$ into (7) yields

$$V_i(k+1) = \sqrt{2P_i(k)\Delta t / C_i + V_i^2(k)} \tag{9}$$

Substituting (8) and (9) into (5) yields

$$SoC_i(k+1) = SoC_i(k) + P_i(k)\Delta t / 0.5C_i \cdot [V_i(K+1) + V_i(k)] \tag{10}$$

Finally, the fitness function finally becomes:

$$J(k) = \sum_i w_i \cdot \left[SoC_i(k) + \frac{P_i(k)\Delta t}{0.5 \cdot C_i \cdot \left[\sqrt{\frac{2P_i(k)\Delta t}{C_i} + V_i^2(k)} + V_i(k)\right]} \right] \tag{11}$$

The utility power (P_{utility}) and the maximum absorbed power ($P_{i,\max}$) by a particular vehicle are the prime energy constraints in this research. The overall efficiency of a specific charging station is designated as η. The efficiency of charging is assumed to be fixed at any given duration from the system point of view. $SoC_{i,\max}$ is the maximum battery State-of-Charge limit for i no. of vehicles. The i no. of battery charger shifts to a standby mode when SoC_i touches the values near to $SoC_{i,\max}$. The overall charging system is transformed to the state in three cases – (i) updates of system utility informations; (ii) a new vehicle is just plugged-in; and (iii) Δt time period has intermittently passed.

Table 1 shows all the fitness function parameters that were tuned for performing the optimization. Here, a single parking lot with the aggregation of distribution network-connected PHEVs is considered. We make use of historical data for office parking from the city of Livermore, CA [29]. There are three types of parameters: fixed, variables and constraints in this optimization problem. The different values for fixed and variable parameters are taken from the previous works of Su [8–10].

3. Standard particle swarm optimization (PSO)

PSO is an evolutionary computation technique which is proposed by Eberhart and Shi [30]. The PSO was inspired from social behavior of bird flocking. It uses a number of particles

Table 1 Parameter settings of the fitness function.

Parameter	Values
Fixed parameters	Maximum power, $P_{i,\max} = 6.7$ kW h Charging station efficiency, $\eta = 0.9$ Total charging time, $\Delta t = 20$ min (1200 s) Power allocation to each PHEV: 30 W
Variables	$0.2 \leqslant$ State-of-Charge (SoC) $\leqslant 0.8$ Waiting time $\leqslant 30$ min (1800 s) 16 kW h $\leqslant$ battery capacity (C_i) $\leqslant$ 40 kW h
Constraints	$\sum_i P_i(k) \leqslant P_{\text{utility}}(k) \times \eta$ $0 \leqslant P_i(k) \leqslant P_{i,\max}(k)$ $0 \leqslant SoC_i(k) \leqslant SoC_{i,\max}$ $0 \leqslant SoC_i(k+1) - SoC_i(k) \leqslant \Delta SoC_{\max}$

(candidate solutions) which fly around in the search space to find best solution. Meanwhile, they all look at the best particle (best solution) in their paths. In other words, particles consider their own best solutions as well as the best solution found so far.

Each particle in PSO should consider the current position, the current velocity, the distance to *pbest*, and the distance to *gbest* in order to modify its position. PSO is initialized with a group of random particles (solutions) and then searches for optima by updating generations. In every iteration, each particle is updated by following two "best" values. The first one is the best solution (fitness) it has achieved so far. (The fitness value is also stored.) This value is called "*pbest*". Another "best" value that is tracked by the particle swarm optimizer is the best value, obtained so far by any particle in the population. This best value is a global best and called "*gbest*".

PSO was mathematically modeled as follows:

$$V_i^{t+1} = wv_i^t + c_1 \times rand \times (pbest_i - x_i^t) + c_2 \times rand \times (gbest - x_i^t) \tag{12}$$

$$x_i^{t+1} = x_i^t + V_i^{t+1} \tag{13}$$

where v_i^t is the velocity of particle i at iteration t, and w is a weighting function usually used as follows:

$$\omega = \omega_{\max} - w_{\max} - (\omega_{\min}/\text{Itre}_{\max})\text{Itre} \tag{14}$$

Appropriate values for $\omega_{\min}$ and $w_{\max}$ are 0.4 and 0.9. Appropriate value ranges for c_1 and c_2 are 1–2, but 2 is most appropriate in many cases. rand is a random number between 0 and 1, x_i^t is the current position of particle i at iteration t, $pbest_i$ is the pbest of agent i at iteration t and $gbest$ is the best solution so far. PSO algorithm works by simultaneously maintaining several particles or potential solutions in the search space. For each iteration of the algorithm, each particle is evaluated by the fitness function being optimized, based on the fitness of that solution.

4. Accelerated particle swarm optimization (APSO)

In APSO, each member of the population is called a particle and the population is called a swarm. Starting with a randomly initialized population and moving in randomly chosen directions, each particle moves through the searching space and remembers the best earlier positions, velocity and accelerations of itself and its neighbors. Particles of a swarm communicate good position, velocity and acceleration to each other as well as dynamically adjust their own position, velocity and acceleration derived from the best position of all particles. The next step starts when all particles have been shifted. Finally, all particles inclined to fly toward better positions over the searching process until the swarm moves close to an optimum of the fitness function. Fig. 2 shows the flowchart of APSO method.

The standard PSO uses both the current global best g^* and the individual best x_i^t. The reason of using the individual best is mainly to increase the diversity in the quality solutions; however, this diversity can be simulated using some randomness. Subsequently, there is no convincing reason for using the individual best, unless the optimization problem of interest is multimodal and highly nonlinear [25].

It is worth pointing out that, there is no need to deal with initialization of velocity vectors. Therefore, the APSO is much simpler. Comparing with many PSO variants, the APSO uses only two parameters, and the mechanism is simple to understand. In APSO for the optimization we have considered three parameters position, velocity and acceleration for each swarm particle, whereas in PSO only two parameters position and velocity are considered for each particle [22]. In this algorithm the swarms are the random sequence and rand positions are generated. From these positions, the velocity and acceleration are generated.

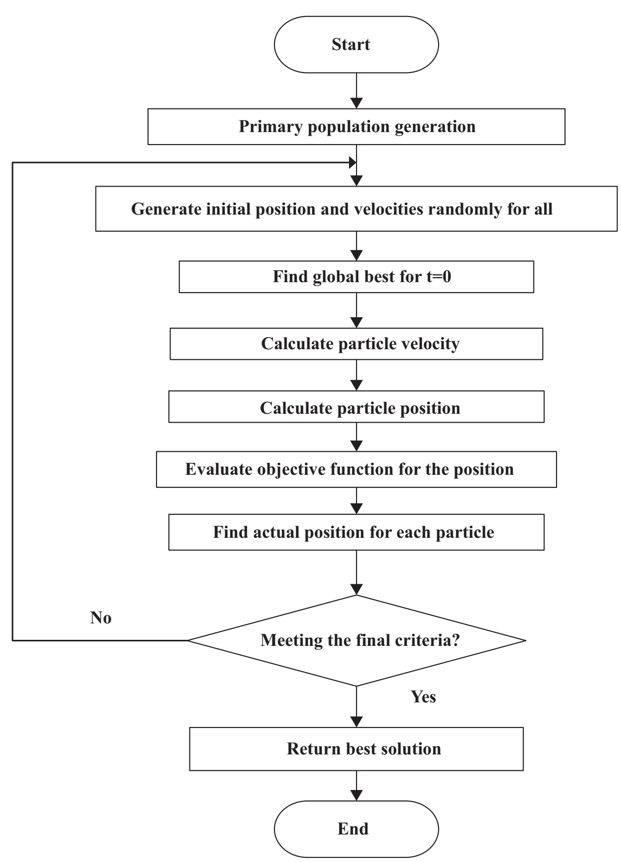

Figure 2 Flowchart of Accelerated particle swarm optimization (APSO).

4.1. The algorithm outline

The outline of Accelerated particle swarm optimization (APSO) is given below:

A simplified version that could accelerate the convergence of the algorithm is to use the global best only. Thus, in the APSO [23,24], the velocity vector is generated by a simpler formula as where *randn* is drawn from (0, 1) to replace the second term. The update of the position is simply like (16).

$$V_i^{t+1} = V_i^t + \alpha \cdot randn(t) + \beta \cdot (g^* - x_i^t) \quad (15)$$

where *randn* is drawn from N (0, 1) and the update of the position is like the standard PSO method. In order to increase the convergence even further, the update of the position can be written in a single step, as

$$x_i^{t+1} = (1-\beta)x_i^t + \beta g^* + \alpha r \quad (16)$$

In our simulation we use [31]

$$\alpha = 0.7^t \quad (17)$$

4.2. APSO parameter settings

The typical values for this accelerated PSO are $\alpha \approx 0.1$–0.4 and $\beta \approx 0.1$–0.7; however, $\alpha \approx 0.2$ and $\beta \approx 0.5$ are recommended [19]. In general, any evolutionary search algorithm shows improved performance with a relatively larger population. However, a very large population will cost more in terms of fitness function evaluations without producing significant improvements. In this simulation, the population size is set to 100. The parameter settings for APSO are demonstrated in Table 2.

5. Simulation results and analysis

5.1. Results

The APSO and PSO techniques were simulated to achieve the best fitness values of fitness function stated at Eq. (11). All the simulations were run on the following computer configuration stated below:

CPU: Core™ i5-3470 M
Processor: 3.20 GHz
RAM: 4.00 GB and
Software: MATLAB version-R2013a.

Table 3 summarizes the simulation results for 50, 100, 500 and 1000 plug-in hybrid electric vehicles (PHEVs) respectively for finding the maximum fitness value of fitness function J (k). In order to evaluate the performance and show the efficiency and superiority of the proposed algorithm, we ran each scenario total 30 times.

Table 2 APSO parameter settings.

Parameters	Values
Size of the swarm	100
Maximum no. of steps	100
Alpha, α	0.2
Beta, β	0.5
Maximum iteration	100
Number of runs	30

So it can be concluded that, APSO outperformed PSO in terms of Average best fitness. Starting from 50 numbers of PHEVs up to 1000 PHEVs, APSO shows better fitness value than PSO.

Table 4 shows the computational time requirement for PSO and APSO methods. As the number of PHEVs increased from 100 to 500 and 1000, APSO technique shows better result than standard PSO method in terms of computational time.

Fig. 3 shows the convergence behavior (iteration vs. fitness value) of APSO technique. It can be apparently seen that although the algorithm has been set to run for maximum 100 iterations, the fitness value converges after 10 iterations and becomes 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 and 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.

Figs. 4–7 show the simulation results for 50, 100, 500 and 1000 plug-in hybrid electric vehicles (PHEVs) respectively for finding the maximum fitness value of fitness function **J**. In order to evaluate the performance and show the efficiency

Table 3 Average best fitness for PSO and APSO.

Average best fitness for	PSO	APSO
50 PHEVs	142.839	165.96509
100 PHEVs	171.102	182.93134
500 PHEVs	150.869	197.59083
1000 PHEVs	156.802	172.45284

Table 4 Computational time for PSO and APSO.

Computational time (s)	PSO	APSO
50 PHEVs	1.650	1.685
100 PHEVs	1.686	1.690
500 PHEVs	1.990	1.856
1000 PHEVs	2.398	2.141

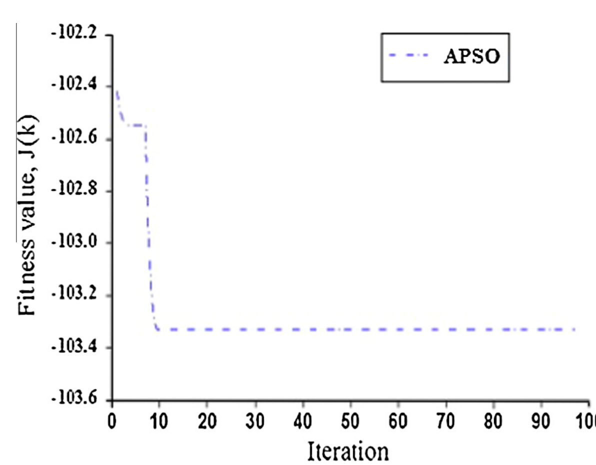

Figure 3 Iteration vs. fitness value, J (k) for APSO (100 PHEVs).

and superiority of the proposed algorithm, we ran each scenario total 30 times. Actually, here ‘Number of steps’ means total number of time steps of the APSO optimization algorithm and ‘number of iterations’ term is used for obtaining successively closer approximations to the solution of our stated problem.

For Fig. 4 (50 PHEVs), the maximum best fitness and minimum best fitness were **469.7489** and **7.6478** respectively.

The average best fitness is **165.9650**. Fig. 5 depicts the maximum fitness value for 100 PHEVs. In this case, the maximum best fitness and minimum best fitness were **679.7151** and **9.5076** respectively. The average best fitness is decreased into **182.9313**.

For Fig. 6 (500 PHEVs), the maximum best fitness and minimum best fitness were **541.4769** and **5.9631** respectively. The average best fitness is **197.5908**.

Fig. 7 depicts the maximum fitness value for 1000 PHEVs. In this case, the maximum best fitness and minimum best fitness were **678.9197** and **0.9963** respectively. The average best fitness is decreased into **172.4528**.

Now, from the aforesaid numerical data we can analyze the simulation behavior of APSO method. As it is a population-based optimization techniques and the fitness function is highly nonlinear, so the fitness values fluctuate for each iteration [32–35]. But, the maximum best fitness remains in the range of 450–700 and the minimum best fitness remains in the range of 1–10. Table 5 summarizes the result. From that it can be concluded that, average best fitness remains almost in similar pattern for four (04) different scenarios.

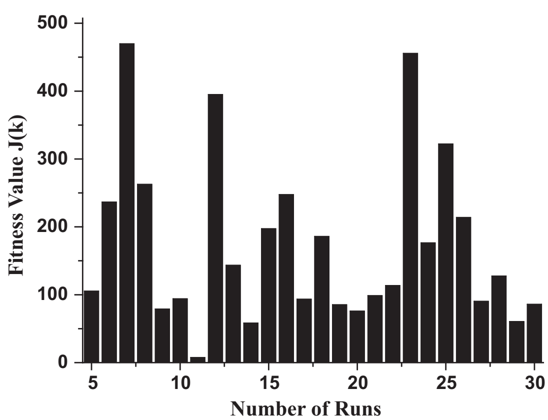

Figure 4 Fitness value vs. no. of runs (50 PHEVs).

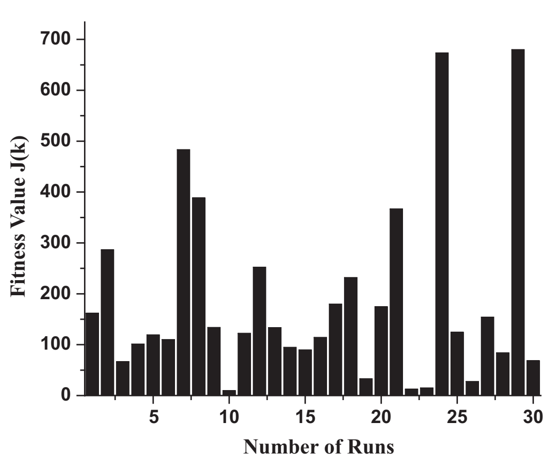

Figure 5 Fitness value vs. no. of runs (100 PHEVs).

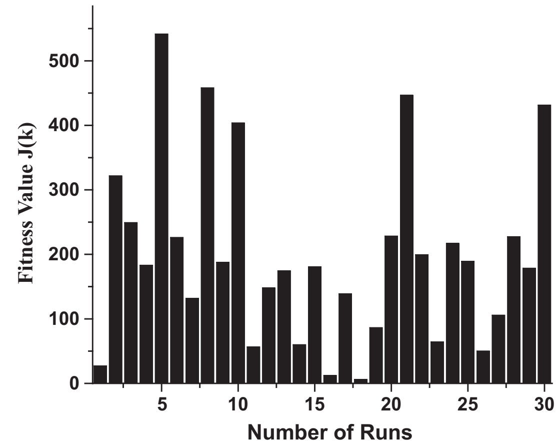

Figure 6 Fitness value vs. no. of runs (300 PHEVs).

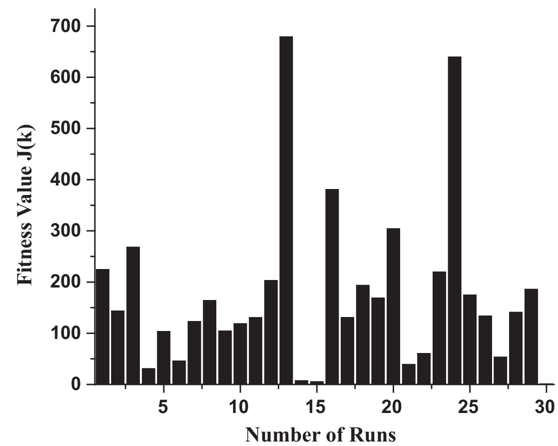

Figure 7 Fitness value vs. no. of runs (500 PHEVs).

Table 5 Fitness evaluation of APSO.

Fitness function J (k)	50 PHEVs	100 PHEVs	500 PHEVs	1000 PHEVs
Max. best fitness	469.7489	679.7151	541.4769	678.9197
Avg. best fitness	165.9650	182.9313	197.5908	172.4528
Min best fitness	7.6478	9.5076	5.9631	0.9963

5.2. Comparison between PSO and APSO

Table 6 illustrates the advantages and disadvantages of both APSO and PSO techniques for solving optimization problems. For solving this particular optimization problem, we faced some issues which will be discussed in this section.

Although APSO needs more parameters tuning compared to Standard PSO method but when the number of PHEVs increases, APSO takes less time than PSO. This characteristic makes APSO very efficient to solve this particular optimization problem. In APSO, the velocity vector ensures local exploitation capability. Moreover, the disadvantage of APSO is that it suffers early convergences in primary stages.

Finally, from Fig. 8 we can come into a conclusion that, APSO performs better than PSO in terms of Average best fitness for up to 1000 Plug-in hybrid electric vehicles.

6. Discussion

6.1. Computational cost

For real-life problems the computational cost of a full evaluation of the fitness function can easily become the dominant computational cost. This computational cost can have the effect of making the time for the swarm to converge slowly [36,37]. In this APSO method, the computational cost is moderate as compared to standard PSO method because of using acceleration factors, α and β.

6.2. Stopping criteria

Since an iterative method computes successive approximations to the solution of a system, stopping criteria are needed to determine when to stop the iteration. The maximum number of iteration was set to 100 for this optimization.

Table 6 Advantages and disadvantages of PSO and APSO.

Optimization method	Advantages	Disadvantages
PSO	Less parameters tuning	Low quality solution
	Easy constraint	Needs memory to update velocity
	Good for multi-objective optimization	Early convergence
APSO	Very efficient High quality solution Local exploitation capability	Suffers from early convergence in the primary stages

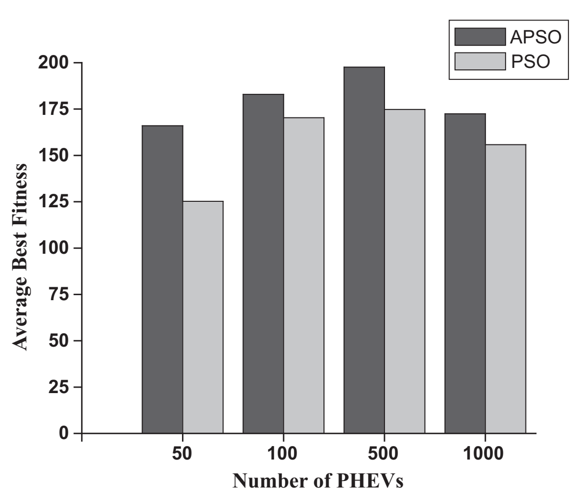

Figure 8 Average best fitness vs. no. of PHEVs (APSO and PSO).

6.3. Robustness

The robustness of the algorithm is examined in terms of the variability of the final solutions from each set of experiments [38]. From Fig. 4 it is clear that, APSO algorithm is not too robust as the maximum, average and minimum fitness values show different values for different number of PHEVs. By tuning the parameters such as α and β will improve the robustness of the optimization which is beyond the scope of this research.

6.4. Computational complexity

Computational complexity refers to the various problems encountered for solving an optimization algorithm, such as early convergence, high computational time, trapping in local optima, and unable to reach global optima/minima [39,40]. In this optimization problem, we encounter premature convergences. Moreover, if the size of swarm is very small, then the algorithm traps in local minima. In order to avoid this, we started our simulation using standard swarm size which is 100. In future, more swarm size will be considered in order to find global solution.

7. Conclusion and recommendations

In this paper, Accelerated particle swarm optimization (APSO)-based optimization was implemented for optimally distributing State-of-Charge (SoC) to 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 toward real-life implementation of such controller for PHEV Charging Infrastructures. Here, four (04) different numbers of PHEVs were considered for MATLAB Simulation and then obtained results were compared with PSO in terms of average best fitness and computational time. Proper charging infrastructure management can assist the larger participation of PHEVs. At the same time, researchers should try to improve available device mechanism for the infrastructure with a view to simplify future PHEVs dispersion in roads and highways. In future, more vehicles should be considered for intelligent power allocation strategy as well as hybrid versions of PSO should be applied to ensure higher fitness value and low computational time.

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