# Handbook of Research on Modern Optimization Algorithms and Applications in Engineering and Economics

Pandian Vasant
*Universiti Teknologi Petronas, Malaysia*

Gerhard-Wilhelm Weber
*Middle East Technical University, Turkey*

Vo Ngoc Dieu
*Ho Chi Minh City University of Technology, Vietnam*

A volume in the Advances in Computational Intelligence and Robotics (ACIR) Book Series

ENGINEERING SCIENCE REFERENCE
An Imprint of IGI Global

Published in the United States of America by
Engineering Science Reference (an imprint of IGI Global)
701 E. Chocolate Avenue
Hershey PA, USA 17033
Tel: 717-533-8845
Fax: 717-533-8661
E-mail: cust@igi-global.com
Web site: http://www.igi-global.com



Library of Congress Cataloging-in-Publication Data

Names: Vasant, Pandian, editor. | Weber, Gerhard-Wilhelm, editor. | Dieu, Vo Ngoc, 1971- editor.
Title: Handbook of research on modern optimization algorithms and applications in engineering and economics / Pandian Vasant, Gerhard-Wilhelm Weber, and Vo Ngoc Dieu, editors.
Description: Hershey : Information Science Reference, 2016. | Includes bibliographical references and index.
Identifiers: LCCN 2015037648| ISBN 9781466696440 (hardcover) | ISBN 9781466696457 (ebook)
Subjects: LCSH: Mathematical optimization. | Algorithms.
Classification: LCC QA402.5 .H3655 2016 | DDC 330.01/5196--dc23 LC record available at http://lccn.loc.gov/2015037648

This book is published in the IGI Global book series Advances in Computational Intelligence and Robotics (ACIR) (ISSN: 2327-0411; eISSN: 2327-042X)

British Cataloguing in Publication Data
A Cataloguing in Publication record for this book is available from the British Library.

# Chapter 18
# Hybrid Particle Swarm and Gravitational Search Optimization Techniques for Charging Plug-In Hybrid Electric Vehicles

**Imran Rahman**
*Universiti Teknologi PETRONAS, Malaysia*

**Balbir Singh Mahinder Singh**
*Universiti Teknologi PETRONAS, Malaysia*

**Pandian Vasant**
*Universiti Teknologi PETRONAS, Malaysia*

**M. Abdullah-Al-Wadud**
*King Saud University, Saudi Arabia*

## ABSTRACT

*Electrification of Transportation has undergone major modifications since the last decade. Success of combining smart grid technology and renewable energy exclusively depends upon the large-scale participation of Plug-in Hybrid Electric Vehicles (PHEVs) towards reach the desired pollution-free transportation industry. One of the key Performance pointers of hybrid electric vehicle is the State-of-Charge (SoC) which needs to be enhanced for the advancement of charging station using computational intelligence methods. In this Chapter, authors applied Hybrid Particle swarm and gravitational search Optimization (PSOGSA) technique for intelligently allocating energy to the PHEVs considering constraints such as energy price, remaining battery capacity, and remaining charging time. Computational experiment results attained for maximizing the highly non-linear fitness function estimates the performance measure of both the techniques in terms of best fitness value and computation time.*

## INTRODUCTION

Recent researches on green technologies for transportation sector are gaining popularity among the research communities from different areas. In this wake, Plug-in hybrid electric vehicles (PHEVs) have great future because of their charge storage system and charging facilities from traditional grid system. Several researchers have proved that a great amount of reductions in greenhouse gas emissions and the

DOI: 10.4018/978-1-4666-9644-0.ch018

increasing dependence on oil could be accomplished by electrification of transport sector (Caramanis & Foster 2009). Future transportation sector will depend much on the advancement of this emerging field of vehicle optimization. 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) (Tie & Tan, 2013). 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 conventional power grid system, that helps the vehicles to operate continuously in "all-electric-range" (AER). All-electric vehicles or AEVs is a kind of transport which use electric power as only sources to run the system. Plug-in hybrid electric vehicles with a connection to the smart grid can own 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 (Lund & Kempton, 2008). There is a need of efficient mechanisms and algorithms for smart grid technologies in order to solve highly diverse problems like energy management, cost reduction, efficient charging station etc. with different objectives and system constraints (Hota, Juvvanapudi, & Bajpai, 2014).

According to Electric Power Research Institute (EPRI), about 62% of the whole United States (US) fleet will comprise of PHEVs within the year 2050 (Soares et al., 2013). Moreover, there is an increasing demand to implement this technology on the electric grid system. 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 (Su & Chow, 2012a). The total demand pattern will also have an important impact on the electricity production due to differences in the needs of the PHEVs parked in the deck at certain time (Su & Chow, 2011). 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 location (Su & Chow, 2012). Wide penetration of PHEVs in the market depends on a well-organized charging infrastructure. The power demand from this new load will put extra stress on the traditional power grid (Morrow, Karner, & Francfort, 2008). As a result, a good number of PHEV charging stations with suitable facilities are essential to be built for recharging electric fleet, for this some strategies have been proposed by the researchers (Mayfield, Jul. 2012). Charging stations are needed to be built at workplaces, markets/shopping malls and home. Boyle (2007) 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, sizeable energy storage, cost minimization; Quality of Services (QoS) and intelligent charging station for optimal power are underway (Hess et al., 2012). In this wake, numerous techniques and methods were proposed for deployment of PHEV charging stations (Z. Li, Sahinoglu, Tao, & Teo, 2010).

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 (Su & Chow, 2012). Charging infrastructures are essential in order to facilitate the large-scale penetration of PHEVs. Different computational intelligence-based methods have been used by some researchers for charging station optimization of PHEV. Most of them applied traditional methods which are needed to be improved furthermore (Rahman, I., Vasant, P.M., Singh, B.S.M., & Abdullah-Al-Wadud, M., 2014).

Swarm intelligence came from the mimic of the living colony such as ant, bird, and fish in nature, which shows unparalleled excellence in swarm than in single in food seeking or nest building. Drawing inspiration from this, researches design many algorithms simulating colony living, such as ant colony algorithm, particle swarm optimization algorithm, artificial bee colony algorithm, and gravitational search algorithm, which shows excellent performance in dealing with complex optimization problems (Jia-zhao, C., Yu-xiang, Z., & Yin-sheng, L., 2012). The intrinsic characteristics of all the population-based meta-heuristic algorithms like Particle swarm optimization (PSO) and Gravitational search algorithm (GSA) are to maintain a good compromise between exploration and exploitation in order to solve the complex optimization problems (Rashedi, E. & Nezamabadi-Pour, 2009).

GSA is based on the law of gravity and mass interactions where the searcher agents are a collection of masses which interact with each other based on the Newtonian gravity and the laws of motion (Rashedi, E. & Nezamabadi-Pour, 2009). This method has also been used by the researchers for post-outage bus voltage magnitude calculations, solving economic dispatch with valve-point effects, optimal sizing and suitable placement for distributed generation (DG) in distribution system, Solving thermal unit commitment (UC) problem and finding out optimal solution for optimal power flow (OPF) problem in a power system (N M., Puteh, M., & Mahmood, M. R., 2013).

Moreover, PSOGSA-based optimization has already been used by the researchers for economic load dispatch (Dubey, Pandit et al., 2013), optimal static state estimation (Mallick, Ghoshal et al., 2013), dual channel speech enhance-ment (Kunche, Rao et al., 2014), training feed-forward neural networks (Mirjalili, Mohd Hashim et al., 2012) and multi-distributed generation planning (Tan, Hassan et al., 2013). 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 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 (Chiasson, J., & Vairamohan, B., 2005). State-of-charge determination becomes an increasingly vital issue in all the areas that include a battery. Previous operation policies made use of voltage limits only to guard the battery against deep discharge and overcharge. Currently, battery operation is changing to what could rather be called battery management than simply protection. For this improved battery control, the battery SoC is a key factor indeed (Piller, Perrin, & Jossen, 2001).

A charging station is one way that the operator of an electrical power grid can adapt energy production to energy consumption, both of which can vary randomly over time. Basically, PHEVs in a charging station are charged during times when production exceeds consumption and are discharged at times when consumption exceeds production (S. Li, Bao, Fu, & Zheng, 2014). 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.

The purpose of this chapter is to optimize state-of-charge, with respect to total cost, charging time, present SoC. Swarm intelligence-based method, Hybrid Particle swarm Optimization and Gravitational search algorithm (PSO-GSA) were applied for solving the optimization problem and then compared with Gravitational search algorithm (GSA) furthermore (Rahman, I., Vasant, P.M., Singh, B.S.M., & Abdullah-Al-Wadud, M., 2014) .

## BACKGROUND

The vehicular network recently accounts for around 25% of $CO_2$ emissions and over 55% of oil consumption around the world. 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 (Holtz-Eakin & Selden, 1995). Charging of PHEV/EV influences many parameters such as power rating, time of charging and location, cost, charging equipment, and effect on the power grid. Issues like charging time, distribution, standardization of demand policies for charging stations and proper regulatory procedures are needed to be addressed for the successful deployment of Electric vehicle charging station (Z. Li et al., 2010).

Most of the electric vehicles charging generally occur at charging area in one's house where the fleet can be connected to a garage outlet for Slow charging (Level-1). Level-2 charging is normally known as the primary technique for battery charging for both public and private utilities and needs an outlet of 240V. Future technologies focus on primary; fast charging and can be executed in most cases (Anegawa, 2009; Botsford & Szczepanek, 2009; Rawson & Kateley, 1999). Usually for Level-1 and 2 charging uses single-phase systems. Level-3(DC fast charging) is made for commercial and public applications and would operate just like a normal filling station. Off-board three-phase solutions are applied to Level-3 chargers and high power. Level-2 or 3 chargers installed in parking lots, shopping centers, hotels, theaters, restaurants, etc. are expected to use by the general public stations (Aggeler, Canales, Coccia, Butcher, & Apeldoorn, 2010).

### Opportunity Charging (Level-1 Charging)

The slowest of all available methods is Level-1 charging. In the United States, Level-1 charging uses a standard 120V/15A single-phase outlet which is grounded, such as NEMA 5-15R. The connection may use a standard J1772 connector into the electric vehicle ac port. No additional infrastructure is required for home or business sites. At night, low off-peak rates for charging are likely to be available. The total cost of a residential Level-1 charging infrastructure has been estimated around \$500 - \$880 (De Sousa, Silvestre, & Bouchez, 2010; Morrow, Karner, & Francfort, 2008).

### Primary Charging (Level-2 Charging)

Level-2 charging is the basic method for dedicated public and private facilities. At present, Level-2 equipment performs charging through 208V or 240V (at up to 80A, 19.2 kW). It may require dedicated equipment and a connection installation for home or public charging (Rawson & Kateley, 1999), although vehicles such as the Tesla have the power electronics on board. Most homes have 240 V service available, and Level-2 devices can charge a typical EV battery overnight. Owners seem likely to prefer Level-2 technology owing to its faster charging time and standardized vehicle-to-charger connection. A separate billing meter is typical. The cost of residential Level-2 infrastructure installation is around $2,150. For example, the Tesla Roadster charging system has imposed additional cost of $3,000 (Motors, 2009).

## Fast Charging (Level-3 Charging)

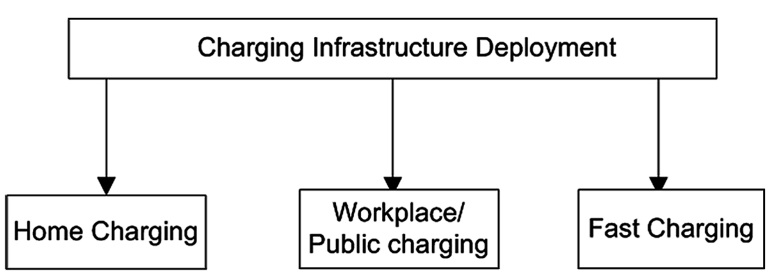
Level-3 (DC fast charging) can be installed in highways and urban refueling points which is similar to petrol stations. It generally operates with a 480 V or higher three phase circuit and needs an off-board charger to provide regulated ac-dc conversion. Level-3 charging is very rear in the residential premises. Standards for dc plugs and hardware are in progress. CHAdeMO-a Japanese protocol is gaining worldwide recognition (Yilmaz & Krein, 2012). Installation cost is a vital issue. Level-3 charging infrastructure costs between $30,000 and $160,000 have been reported. An efficient energy management system is proposed (Dusmez, Cook, & Khaligh, 2011) which notably reduce total time of PHEVs charging in fast charging infrastructure by the use of additional super capacitors and flywheel. The simulations for two batteries between 10kWh and 15kWh show that the charging time on average is 15 min to charge from a minimum SOC 20% to maximum 95% in the latest configuration. Finally, Figure 1 summarizes the charging methods.

## Charging Infrastructures

Maintenance of the charging infrastructures is another cost factor (Brown, Mikulin, Rhazi, Seel, & Zimring, 2010). There are increasing numbers of literatures on various aspects of the EV charging allocation strategies which includes the maintenance and scheduling of various chargers (Caramanis & Foster, 2009; Gan, Topcu, & Low, 2011; Kefayati & Caramanis, 2010; Ma, Callaway, & Hiskens, 2010; Pang, Dutta, Kim, Kezunovic, & Damnjanovic, 2010; Sojoudi & Low, 2011). Most of the works focus specially on residential charging schemes. Kulshrestha, Wang, Chow, and Lukic (2009) conducted studies based on simulation in energy management strategy (EMS) for PHEV/EV charging at parking areas where meta-heuristic algorithms for the purpose of efficient scheduling are applied. The electric vehicle charging for public garages is also considered (Su & Chow, 2011) where the objective is to maximize the throughput of service whereas the total cost of energy is not considered in the optimization. Subramanian et al. (2012) suggested a scheduling optimization using a combination of alternative energy and energy from the traditional grid.

The next section provides an overview of the charging infrastructure requirements for PHEVs/EVs in single-family household, multi-family household and commercial situations.

*Figure 1. Changing infrastructure for PHEVs*



These scenarios include the following:

- Household garage charging
- Apartment complex charging
- Commercial complex charging
- Charging from renewable energy sources

## Household Garage Charging

In order to install electric vehicle charging supply in a household garage, dedicated branch circuit from an existing house distribution panel to a convenience outlet or to a EVSE (Electric Vehicle Supply Equipment) is necessary (Morrow et al., 2008).

## Apartment Complex Charging

Installation of the EV/PHEV charging supply in an apartment complex typically consists of installing new dedicated branch circuits from the central meter distribution panel to either a convenience outlet or to an EVSE (Morrow et al., 2008).

## Commercial Complex Charging

Installation of the electric vehicle charging supply in a commercial complex parking lot typically consists of installing new dedicated branch circuits from the central meter distribution panel to an EVSE for Level-2 charging. Large parking lots provide an opportunity to control a fleet of PHEVs in an intelligent manner.

Effective use of PHEVs in parking areas to prevent the transmission lines getting overloaded and to act as shock observers when the wind power changes drastically is explored by Venayagamoorthy and Mitra (2011). A fuzzy logic controller was proposed (Mitra & Venayagamoorthy, 2010) which takes the total state of charge of a parking lot, instantaneous demand and wind power generated as inputs and gives control signals for charging/discharging of the PHEVs. Simulations on a12 bus system model show that when PHEVs charge and discharge according to the control signal, overloading of the transmission lines during high wind speeds can be prevented and the wind power supply fluctuations to the grid can be minimized.

## Charging from Renewable Energy Sources

The ability of PHEVs/EVs to assist the integration of renewable energy sources into the existing power grid is potentially the most transformative impact on the electricity system. Deployment of large-scale photovoltaic (PV) charging equipment in a parking lot is explained by Neumann, Schär, and Baumgartner (2012). PV parking lot charging and different business models to charge PHEVs/EVs with solar energy are also studied by Letendre (2009). Economics and environmental impacts of PV based workplace charging station has also been discussed (Birnie, 2009; Tulpule, Marano, Yurkovich, & Rizzoni, 2013). The analysis shows the technical feasibility of a PV powered workplace parking lot with benefits to the owner of the vehicle as compared to facilities of household charging. Authors conclude that the owner will get the return of establishment and maintenance cost and profit within the lifespan of the photovoltaic panels. According to Birnie (2009), introducing a solar collector into a parking shade would result in a much more rapid pay-back-period, encouraging widespread installation of solar capacity. Zhang, Tezuka, Ishihara, and Mclellan (2012) explained smart control strategies for the integration of both EVs and PV together with the present electricity systems. Co-benefits of introducing large penetration of PHEVs and photovoltaic mechanisms have been analyzed by Denholm, Kuss, and Margolis (2013). The study came to a conclusion that PV has the capability of acting like a potential source of mid-day generation capacity for PHEVs as well as provide a dispatch able load during low demand periods (generally in the spring season). For this wake, a 2.1 kW PV charging station combined with the utility at Santa Monica is explained (Ingersoll & Perkins, 1996). Zhu, Yu, Ning, and Tang (2012) presented optimal charging control policy using stochastic semi-Markov decision (SMDP) process and later average reward was calculated using vehicle admission probability.

Smart grid has brought new opportunities and challenges for the development of electric vehicle Infrastructure facilities like charging station systems and parking lots. Recent advancement in renewable energy sector opens the option for a green infrastructure system which will minimize the burden of PHEVs in tradition grid-dependent charging stations.

Proper SoC will ensure smooth growth of PHEV in near future. Without proper maintenance and infrastructure facilities, large number of PHEVs charging will burden the existing grid hence instability of power grid. For this, researchers should apply proper techniques methods in order to solve various optimization problems related to this field. Energy allocation to PHEV charging station is subjected to various constraints such as charging time, SoC and price which will be highlighted in the problem formulation section. Different constraints make the entire search space limited to a particular suitable region. So, powerful optimization algorithms should be implemented in order to achieve high quality solutions with a stable convergence rate.

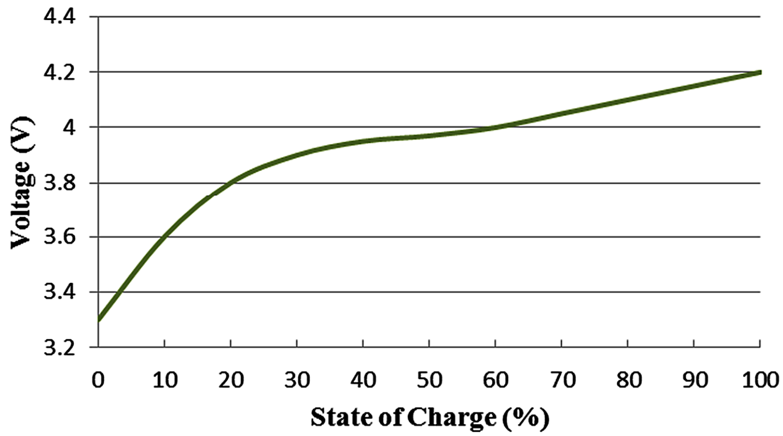
## MAIN FOCUS OF THE CHAPTER

### Problem Statement

One of the important constraints for accurate charging is State-of-Charge (SoC). Charging algorithm can precisely be managed by the precise state of charge evaluation (Shafiei & Williamson, 2010). An approximate graph of a typical Lithium-ion cell voltage versus SoC is shown in Figure 2 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. 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.

The idea behind smart charging is to charge the vehicle when it is most favourable, which could be when electricity price, demand is lowest, when there is excess capacity (Su & Chow, 2012). When a vehicle is plugged in into a smart charging station a request for energy demand is sent to Substation Control Center (SCC), which decides based on the available energy from utility and either accepts the request or reject it. Performance of this kind of load management is measured in terms of delay, delivery ration and jitter. As a matter of fact EVs may be charged at any time of a day depending on requirement

*Figure 2. Li-ion cell voltage vs. State-of-Charge*




to top their batteries even during peak demand hours. Increasing load on the grid during peak hours may require extra power generation through any source which may increase the cost and greenhouse gases emission (Ul-Haq, Buccella, Cecati, & Khalid, 2013).

Suppose, there is a charging station with the capacity of total power P. Total N numbers of PHEVs need to be served 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 efficiently. For this, the fitness function considered in this chapter 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 (Rahman, I., Vasant, P.M., Singh, B.S.M., & Abdullah-Al-Wadud, M., 2014).

The fitness function is defined as:

$$\text{Max } J\left(k\right)=\sum_{i} w_{i}\left(k\right) SoC_{i}\left(k+1\right) \tag{1}$$

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

$$C_{r,i}\left(k\right)=\left(1-SoC_{i}\left(k\right)\right)\cdot C_{i} \tag{3}$$

where $C_{r,i}\left(k\right)$ 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 $T_{r,i}\left(k\right)$; 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 $D_{i}\left(k\right)$; $w_{i}\left(k\right)$ is the charging weighting term of the $i$ no. of PHEV at time step $k$ (a function of

*Table 1. Parameter settings of the fitness function*

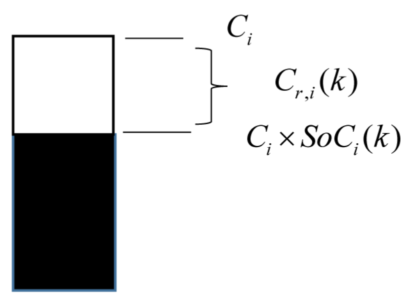
| Parameter | Values |
|---|---|
| Fixed Parameters | Maximum power, $P_{i,\max}$ = 6.7 kWh |
| | Charging station efficiency, $\eta$ = 0.9 |
| | Total charging time, $\Delta t$ = 20 Minute |
| | Power allocation to each PHEV: 30 W |
| Variables | 0.2 ≤ State-of-Charge (SoC) ≤ 0.8 |
| | Waiting time ≤ 30 Minutes (1800 Seconds) |
| | 16 kWh ≤ Battery Capacity ( $C_i$ ) ≤ 40 kWh |
| Constraints | $\sum_i P_i\left(k\right) \leq P_{utility}\left(k\right) \times \eta$ |
| | $0 \leq P_i\left(k\right) \leq P_{i,\max}\left(k\right)$ |
| | $0 \leq SoC_i\left(k\right) \leq SoC_{i,\max}$ |
| | $0 \leq SoC_i\left(k+1\right) - SoC_i\left(k\right) \leq \Delta SoC_{\max}$ |

charging time, present SoC and price of the energy); $SoC_i\left(k+1\right)$ is the state of charge of the $i$ no. of PHEV at time step $k+1$. The illustration of the remaining battery capacity is given in Box 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 $\mathrm{SoC}$ 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:

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

*Box 1.*



The charging current is also assumed to be constant over $\Delta t$ .

$$\left[SoC_i\left(k{+}1\right)-SoC_i\left(k\right)\right]\cdot Cap_i = Q_{\mathrm{i}} = I_i\left(k\right)\Delta t \tag{5}$$

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

where the sample time $\Delta t$ is defined by the charging station operators, and $\mathrm{I_i}\left(k\right)$ is the charging current over $\Delta t$ .

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

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

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

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

$$V_{\mathrm{i}}\left(k+1\right) - V_i\left(k\right) = I_i \Delta t\,/\,C_i \tag{9}$$

Since the decision variable is the power allocated to the vehicles, replacing $I_i(k)$ with $P_i(k)$

$$\mathrm{I_i}\left(k\right) = P_i\left(k\right) / \,0.5 \times [V_{\mathrm{i}}\left(k+1\right) - V_i\left(k\right)] \tag{10}$$

$$V_{\mathrm{i}}\left(k+1\right) = \sqrt{\frac{2P_i\left(k\right)\Delta t}{C_i} + V^2{}_i\left(\mathrm{k}\right)} \tag{11}$$

Substituting (10) into (6) yields

$$SoC_i\left(k+1\right) = SoC_i\left(k\right) + \frac{P_i\left(k\right)\Delta t}{0.5.\,C_i \cdot \left[\sqrt{\frac{2P_i\left(k\right)\Delta t}{C_i} + V^2{}_i\left(\mathrm{k}\right)} + V_{\mathrm{i}}\left(k\right)\right]} \tag{12}$$

Finally, the objective function becomes

$$J\left(k\right)=\sum w_i.\left[SoC_i\left(k\right)+\frac{P_i\left(k\right)\Delta t}{0.5.C_i.\left[\sqrt{\frac{2P_i\left(k\right)\Delta t}{C_i}+V^2_i\left(\mathrm{k}\right)+V_\mathrm{i}\left(k\right)}\right]}\right] \tag{13}$$

There are two kind of inequality constraints used here to optimize the fitness function- i) Power from the charging station operator and ii) individual PHEV's State-of-Charge (SoC). 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 chapter. The overall charging efficiency of a particular charging station is described by $\eta$ . 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 $\Delta SoC_{\max}$ . The overall control system is changed the state when i) system utility data updates; ii) a new PHEV is plugged-in; iii) time period $\Delta t$ has periodically passed. Obviously, SoC maximization method being considered in this chapter can provide a uniformly higher SoC for all PHEVs/PEVs at plug-out as compared with the alternative schemes. It also proves that the proposed function aims at ensuring some fairness in the SoC-distribution at each time step. This will help to ensure that a reasonable level of battery power is attained, even in the event of an early departure.

Table 1 shows all the fitness function parameters that were tuned for performing the optimization. There are total three (03) kinds of parameter: fixed, variables and constraints. Total charging time is fixed to 20 minutes and charging station efficiency assumed to be 0.9. The values are retrieved from various literatures (Hota, Juvvanapudi, & Bajpai, 2014; Su, 2012; Wencong & Mo-Yuen, 2011). Moreover, State-of-Charge is in the range of 0.2 to 0.8 (Chang, 2013).

The implementation of the proposed two optimization methods (GSA, PSOGSA) to our problem is given below in points:

1. Initializing the random and fixed values of both the algorithm and fitness function parameters.
2. Generation of a random solutions (masses) group in the feasible region. Since we normally have very little information about the global optima, these particles are scattered over the search space as uniformly as possible.
3. Evaluate the distance between the new solution and the desired solution based upon a fitness function.
4. Best fitness value as a solution.
5. Repeat steps 2-3 for another iteration until iteration=100.

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 (Downtown parking Study, Livermore, CA, 2006)

## PROPOSED METHODS

### Gravitational Search Algorithm

GSA is an optimization method which has been introduced by Rashedi et al. in the year of 2009. In GSA, the specifications of each mass (or agent) are total four, which is mass (inertial), position, mass (active gravitational) and mass (passive gravitational). The position of the mass presents a solution of a particular problem, and masses (gravitational and inertial) are obtained by using a fitness function. GSA can be considered as a collection of agents (candidate solutions), whose masses are proportional to their value of fitness function. During generations, all masses attract each other by the gravity forces between them. A heavier mass has the bigger attraction force. Therefore the heavier masses which are probably close to the global optimum attract the other masses proportional to their distances.

Law of gravity: The law states that particles attract each other and the force of gravitation between two particles is directly proportional to the product of their masses and inversely proportional to the distance between them.

Law of motion: The law states that the present velocity of any mass is the summation of the fraction of its previous velocity and the velocity variance. Variation in the velocity or acceleration of any mass is equal to the force acted on the system divided by inertia mass.

The gravitational force is expressed as follows:

$$F_{ij}^{d}(t) = G(t)\frac{M_{pi}(t)\times M_{aj}(t)}{R_{ij}(t)+\mu}\left(x_{j}^{d}(t)-x_{i}^{d}(t)\right) \tag{14}$$

where $M_{aj}$ is the active gravitational mass related to agent j, $M_{pi}$ is the passive gravitational mass related to agent $i$, G(t) is gravitational constant at time $t$, $\varepsilon$ is a small constant and $R_{ij}(t)$ is the Euclidian distance between two agents i and j. The $G(t)$ is calculated as-

$$G(t) = G_{0}\times \exp\left(-\alpha \times \mathrm{iter} / \mathrm{maxiter}\right) \tag{15}$$

where $\alpha$ and $G_{0}$ are descending coefficient and primary value respectively, current iteration and maximum number of iterations are expressed as iter and maxiter. In a problem space with the dimension d, the overall force acting on agent i is estimated as following equation:

$$F_{i}^{d}(t) = \sum_{j=1, j\neq i}^{N} \mathrm{rand}_{j} F_{ij}^{d}(t) \tag{16}$$

where $\mathrm{rand}_j$ is a random number with interval [0, 1]. From law of motion we know that, an agent's acceleration is directly proportional to the resultant force and inverse of its mass, so the acceleration of all agents should be calculated as follow:

$$\mathrm{ac}_i^d\left(t\right) = \frac{F_i^d\left(t\right)}{M_{ii}\left(t\right)} \tag{17}$$

where t is a specific time and $M_{ii}$ is the mass of the object i. The velocity and position of agents are calculated as follow:

$$\mathrm{vel}_i^d\left(t+1\right) = \mathrm{rand}_i \times \mathrm{vel}_i^d\left(t\right) + \mathrm{ac}_i^d\left(t\right) \tag{18}$$

$$x_i^d\left(t+1\right) = x_i^d\left(t\right) + \mathrm{vel}_i^d\left(t+1\right) \tag{19}$$

where $\mathrm{rand}_i$ is a random number with interval [0, 1].

In Gravitational search algorithm, all agents are initialized first with random values. Each of the agents is a candidate solution. After initialization, velocities for all agents are defined using (18). Moreover, the gravitational constant, overall forces, and accelerations are determined by equations (15), (16) and (17) respectively. The positions of agents are calculated using (19). At the end, GSA will be terminated by meeting the stopping criterion of maximum 100 iterations. The parameter settings for GSA are demonstrated in Table 2. The GSA parameters were selected: Primary parameter, $G_0 = 100$, Acceleration coefficient, $\alpha$ =20 and No. of mass agents=100. Since each agent could observe the performance of the others, the gravitational force is an information-transferring tool.

*Table 2. GSA parameter settings*

| Parameters | Values |
|---|---|
| Primary parameter, $G_o$ | 100 |
| No. of mass agents, $n$ | 100 |
| Acceleration coefficient, $\alpha$ | 20 |
| Constant parameter, $\varepsilon$ | .01 |
| Power of 'R' | 1 |
| Maximum iteration | 100 |
| Number of runs | 50 |

## The Algorithm Outline

The outline of gravitational search algorithm is given below:

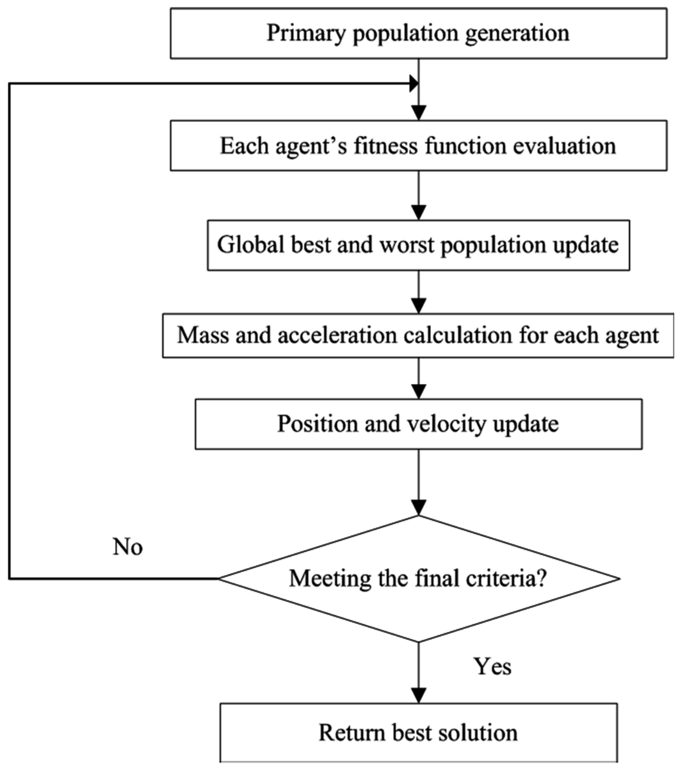
```
1.  Initialization of  total N mass agents randomly
2.  Computation of  G(t), Fitness (Best and Worst)
3.  For each of the agent i, evaluate:
    3.1.  Finess_i
    3.2.  Mass_i
    3.3.  Force of Mass_i
    3.4.  Acceleration of Mass_i
    3.5.  Mass_i velocity update
    3.6. New position of  Agent_i
              If (Probability_i > Threshold)
                             {
              If (Probability_i > Random_i)
           Then return Best Fitness solution so far
           Else
                 Modification of solution
                         }
4.  Failed to meet stopping criteria,
           Go To Step 2, Else Stop
```

Moreover, the step involves in optimization using GSA is shown Figure 3. Here, we assume that the gravitational and the inertia masses are the same. However, for some applications different values for them can be used. A bigger inertia mass provides a slower motion of agents in the search space and hence a more precise search. Conversely, a bigger gravitational mass causes a higher attraction of agents. This permits a considerable convergence (Rashedi, Nezamabadi-Pour, & Saryazdi, 2009). When an algorithm finds an optimal solution to a given problem, one of the important factors is speed and rate of convergence to the optimal solution. For heuristics, the additional consideration of how close the heuristic solution comes to optimally is generally the primary concern of the researcher (Barr, Golden et al. 1995). In GSA, the stable convergence and better exploitation rate ensures good quality solution, which is expressed in terms of best fitness function.

## The Hybrid PSOGSA Algorithm

Before starting the mechanism of hybrid PSOGSA algorithm, it is necessary to shade some light on standard Particle Swarm Optimization (PSO). The system initially has a population of random selective solutions. Each potential solution is called a particle. Each particle is given a random velocity and is flown through the problem space. The particles have memory and each particle keeps track of its previous best position (called the *pbest*) and its corresponding fitness. There exist a number of pbest for the respective particles in the swarm and the particle with greatest fitness is called the global best

*Figure 3. Structural diagram of GSA*




(*gbest*) of the swarm. The basic concept of the PSO technique lies in accelerating each particle towards its pbest and gbest locations, with a random weighted acceleration at each time step (Ganesan, Vasant, & Elamvazuthy, 2012).

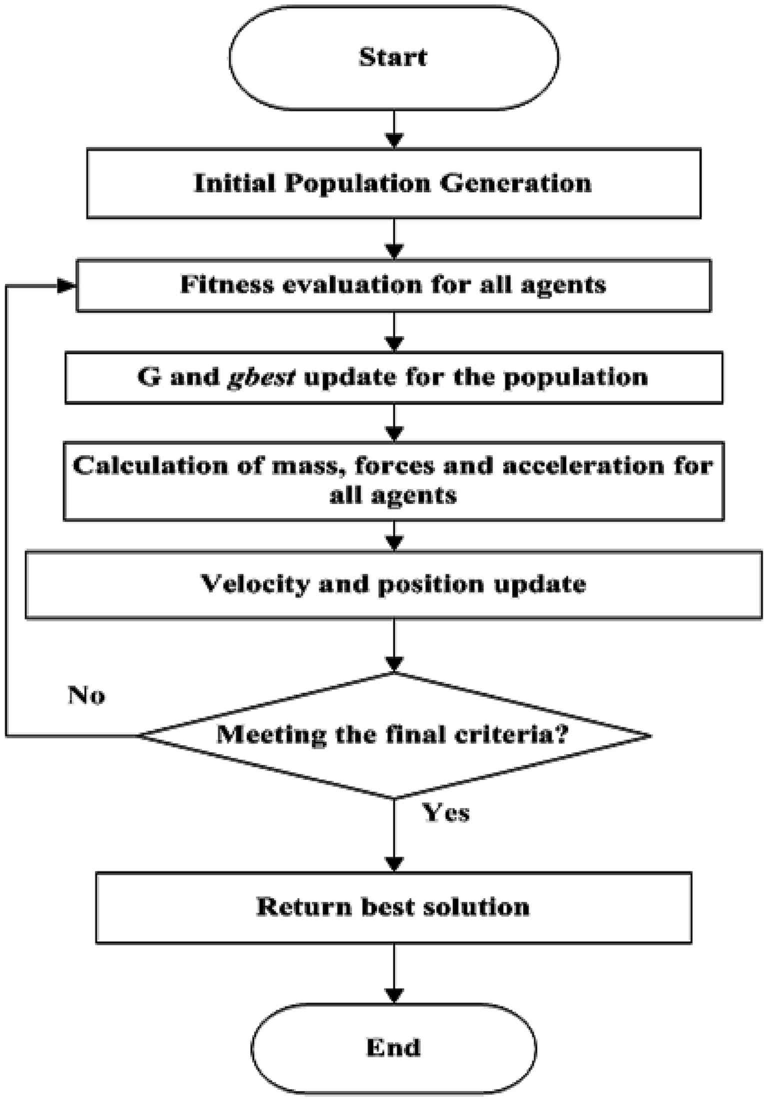
In this chapter, a new hybrid population-based algorithm (PSOGSA) [14] is proposed with the combination of Particle Swarm Optimization (PSO) and Gravitational Search Algorithm (GSA). The basic idea is to fit in the exploitation ability in PSO with the exploration ability in GSA to synthesize both algorithms'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

$$v_i(t+1) = w \times v_i(t) + \alpha' \times rand \times ac_i(t) + \beta' \times rand \times (gbest - x_i(t)) \tag{20}$$

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. Here, $\alpha'$ and $\beta'$ are the weighting factors. With adjusting $\alpha'$ and $\beta'$, the abilities of global search and local search can be balanced. The position of the particle $x_i(t+1)$ in each iteration is updated using the equation

$$x_i(t+1) = x_i(t) + v_i(t+1) \tag{21}$$

*Figure 4. Structural diagram of PSOGSA*




The flowchart of hybrid PSOGSA method is shown in figure 4.

The agents are adjusted randomly and each agent in the search space is attracted towards the agent having a good solution. The agents near the optimal solution moves more slowly and assures the exploitation step of algorithm. Here gbest is used to exploit the global best. The position and velocity are updated until it reaches to the stopping criterion (Dubey, Pandit et al., 2013).

## The Algorithm Outline

The outline of gravitational search algorithm is given below:

```
1.  Generate initial population
2.  Evaluate fitness for all population
3.  Update the G and gbest for the population
4.  For each of the agent i, evaluate:
     4.1.  Finess_i
     4.2.  Mass_i
     4.3.  Force of Mass_i
     4.4.  Acceleration of Mass_i
5.  Update velocity and position
6.  Failed to meet stopping criteria,
            Go To Step 2, Else Stop
```

## Solutions and Recommendations

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

Figure 5 show the convergence behavior of GSA. The result derived in this chapter reveals that each object of the standard GSA converges to a stable point. Here, the assumption was that the gravitational and inertia masses are the same. However, for some applications different values for them can be used. A heavier inertia mass provides a slower motion of agents in the search space and hence a more precise search (Rashedi et al., 2009). On the contrary, a heavier gravitational mass causes a higher attraction of agents. This allows a faster convergence. The analysis results confirm the convergence characteristics of GSA according to the given parameters ranges of the algorithm. The best fitness function convergences after 35 iterations for 100 numbers of PHEVs.

From figure 6, it can be apparently seen that although the PSOGSA algorithm has been set to run for maximum 100 iterations, the fitness value converges before 10 iterations and be-come stable. So, PSOGSA takes less iterations to converge than GSA method due to the weak local search ability. Moreover, 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 in-creased as well. As a result, a trade-off should be taken into consideration between the proper convergence and computational time.

PSOGSA with the parameter settings stated in Table 3 was also performed for the same fitness function and compared with the performance of gravitational search algorithm in terms of average best fitness. The swarm size and maximum iterations was set exactly same to that of GSA technique for the comparison purpose. The values of parameters c1, c2 and alpha were set as standard values, 0.5, 1.5 and 23 respectively.

*Figure 5. Iteration vs. fitness value, J (k) for GSA [100 PHEVs]*

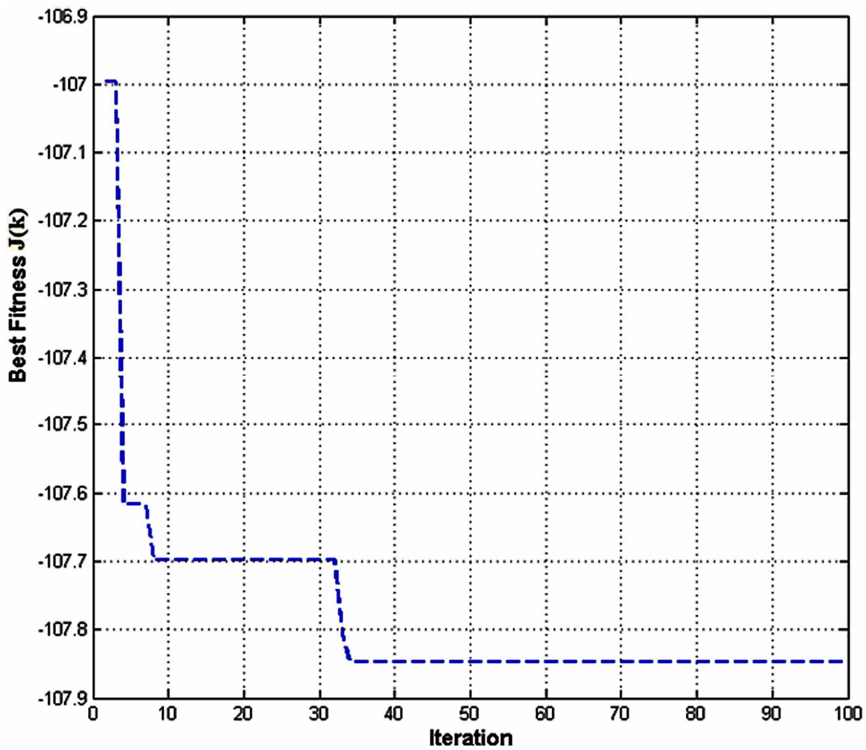



*Figure 6. Iteration vs. fitness value, J(k) for PSOGSA [100 PHEVs]*

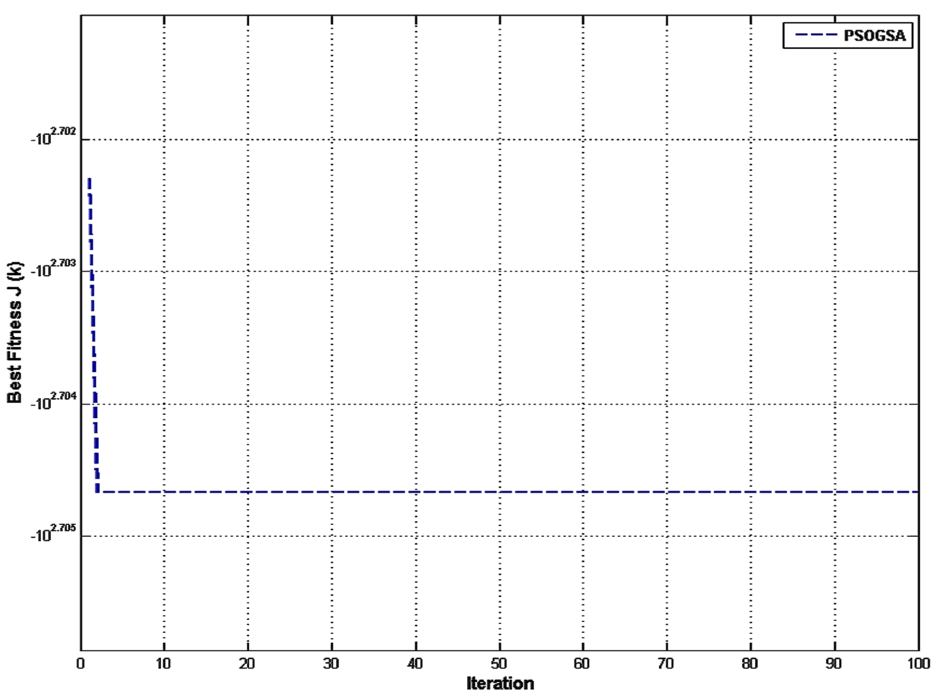


*Table 3. Parameter settings of PSOGSA*

| Parameters | Values |
|---|---|
| Size of the swarm | 100 |
| Maximum iteration | 100 |
| PSO parameter, C1 | 0.5 |
| PSO parameter, C2 | 1.5 |
| Gravitational Constant, $G_o$ | 1 |
| GSA Constant parameter, α | 23 |
| Number of runs | 50 |

## Comparison between PSOGSA and GSA

Table 4 summarizes the comparisons of GSA and PSO with PSOGSA algorithm in terms of average best fitness. Here, the average best fitness gives different values with the increment of PHEVs population. The convergence rate of mass agents in GSA is good through the fast information flowing among mass agents, so its diversity decreases very quickly in the successive iterations and lead to a suboptimal solution. In the case of PSOGSA, the algorithm cannot make full use of the feedback information in the system. There is also possibility of this algorithm to trap in the local optimal solution and lacks the searching capabilities within the whole search area.

Table 5 illustrates the advantages and disadvantages of both GSA and PSOGSA for solving different optimization problems. Energy scheduling at a PHEV charging station is subjected to different constraints that limit the search space to a certain feasible region. PSOGSA can easily handle the constraints separately, eliminating the need for additional parameters (Su & Chow, 2012). PSOGSA method is good for multi-objective optimization while GSA takes slightly more computational time with parameters tuning. The performance of both algorithms varies with the applications and different fitness functions.

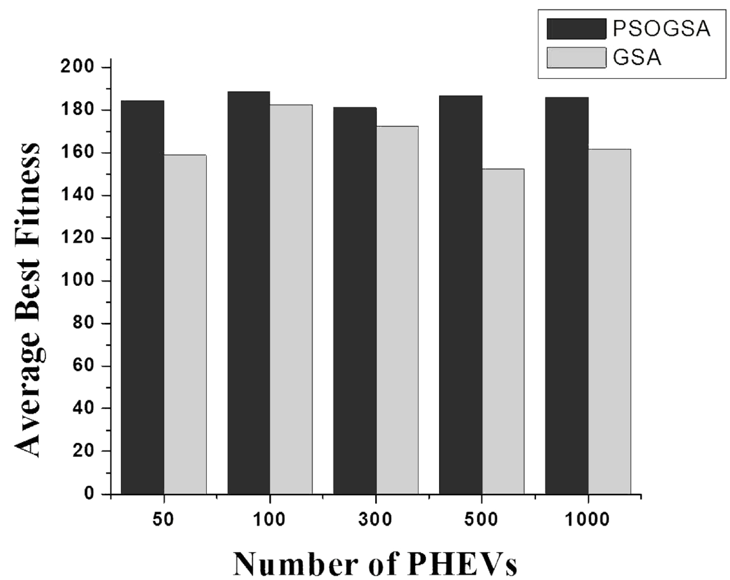
*Table 4. Average best fitness comparison between PSOGSA and GSA*

| Average Best Fitness for | PSOGSA | GSA | PSO (Rahman et al., 2014) |
|---|---|---|---|
| **50 PHEVs** | 184.36 | 158.83 | 142.839 |
| **100 PHEVs** | 188.67 | 182.31 | 171.102 |
| **500 PHEVs** | 186.71 | 152.36 | 150.869 |
| **1000 PHEVs** | 185.82 | 161.52 | 156.802 |

*Table 5. Advantages and disadvantages of PSOGSA and GSA*

| Optimization Method | Advantages | Disadvantages |
|---|---|---|
| **PSOGSA** | Easy constraint<br>Good convergence rate | More parameters tuning<br>Computational time |
| **GSA** | strong exploration ability<br>among all evolutionary algorithms<br>Local exploitation capability | Slow convergence rate<br>More parameters tuning |

*Figure 7. Average best fitness vs. No. of PHEVs*




The average best fitness of both algorithms are represented with respect to number of vehicles (PHEVs) in Figure 7. From the figure it is clear that, Hybrid Particle Swarm Optimization and Gravitational Search Algorithm (PSOGSA) outperforms Gravitational Search Algorithm (GSA) in terms of Average best fitness. Here, the average best fitness gives different values with the increment of PHEVs population. The rate of convergence of mass agents in PSOGSA is good through the fast information flowing among mass agents, so its diversity decreases very quickly in the successive iterations and lead to a suboptimal solution. Starting from 50 numbers of PHEVs up to 1000 PHEVs, PSOGSA shows better fitness value than GSA.

Table 6 shows the computational time requirement for PSOGSA, GSA and PSO method. As the number of PHEVs increased from 100 to 500 and then 1000, standard PSO as well as GSA technique show better result than PSOGSA method in terms of computational time.

So, it can be concluded that, GSA obtains better result in terms of computational time while PSOGSA performs well for achieving the best fitness values compared to GSA.

*Table 6. Computational time for PSOGSA and GSA*

| Computational Time (sec.) | PSOGSA | GSA | PSO (Rahman et al., 2014) |
|---|---|---|---|
| 50 PHEVs | 4.29 | 2.271 | 1.650 |
| 100PHEVs | 7.90 | 4.439 | 1.686 |
| 500 PHEVs | 36.82 | 18.165 | 1.990 |
| 1000 PHEVs | 72.41 | 36.275 | 2.398 |

## FUTURE RESEARCH DIRECTIONS

This paragraph summarizes the review results and suggests future directions of optimization techniques and procedures. The specific research field is relatively new and possible future perspectives have to be emphasized, so that new techniques can be realized.

### Optimization Techniques

Possible characteristics of the future optimization tools are given below:

- The future optimization tools should be capable of performing parallel processing evaluations on the same computer by using modern multi-core processor technology or to distribute the calculations to a cluster of computers. Such ability will substantially improve the simulation runtime.
- Emerging mathematical methods like evolutionary algorithms, direct search methods, local search and other heuristic methods should be introduced in order to avoid the calculation of function derivatives. The experienced researcher should be able to choose the appropriate algorithm depending on the problem. Multi-objective capability should also be provided for multi-criteria optimization problems. Different swarm intelligence-based optimization methods like Ant Colony Optimization (ACO), Artificial Bee Colony (ABC) should also be explored by the researchers to solve problems related to PHEV charging.
- The future optimization tools should have the capability of stable convergence and thus provides good solution to the desired fitness functions.
- Exploration and exploitation of the search space is crucial in order to get desired solution within acceptable computation time.
- Advanced controlling mechanisms are necessary for allocating sufficient energy to a particular charging station in order to facilitate large-scale PHEV penetration in upcoming years.
- Finally, optimization of charging station needs proper selection of available resources as well as efficient available technique implementation.

### Demand Side Management

Demand Side Management (DSM) is defined by Department of Energy (DOE) [69] as "Changes in electric usage by end-use customers from their normal consumption patterns in response to changes in the price of electricity over time, or incentive payments designed to induce lower electricity use at times of high wholesale market prices or when system reliability is jeopardized." Therefore, the demand side management programs should be incorporated into the existing Intelligent Energy Management System (iEMS) model in order to avoid voltage sag and blackout and to maximize the financial benefits. In addition, this under-utilized capacity could effectively power a national fleet of PHEVs with little need to increase the energy delivery capacity of the existing grid infrastructure (Gerkensmeyer, Kintner-Meyer, & DeSteese, 2010).

### Trade-Off between Cost and Performance

Observing the effects of cost and performance on the marketability of PHEVs, the fitness function is defined to minimize drivetrain cost and driving performance requirements are selected as constraints to ensure that the vehicle performance is not sacrificed during the optimization. The battery is the key component within an electric vehicle (EV) which determines its overall capital cost and performance. Therefore, the task of determining the cost effectiveness of EVs is predominantly one of identifying the future trajectory of battery cost and performance. To meet power requirements: batteries have lower discharge power at low SoC and lower charge power at high SoC. To reduce safety risks, limiting the maximum SoC avoids overcharge situations.

## CONCLUSION

Researchers are trying to design efficient controller for charging station and several literatures on optimization-based methods were published in this wake. These vehicles will help the government in its role of promoting energy security and environmental protection, when successfully marketed to consumers. Efforts are also to be taken for provision of affordable and accessible infrastructure for recharging. Hence, thrust in research and development on the aforementioned design considerations and technological challenges coupled with government support in terms of incentives to the automobile owners and to the manufacturers will go a long way in accelerating the deployment of large-scale PHEVs. In the future, more fitness functions (such as minimizing the overall charging time, etc.) should be considered in order to satisfy both client interests and the requirements of the power grid. However, conflicts can arise when multiple fitness functions are applied. The easiest solution to this problem involves combining all of the objectives into a single function. In this case, the weights assigned to each can be fixed or dynamically changed during the optimization process.

In this chapter, Hybrid Particle swarm and Gravitational search algorithm (PSOGSA)-based optimization were 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 is a step towards real-life implementation of such controller for PHEV charging stations. Here, four (04) different numbers of PHEVs were considered for MATLAB Simulation and then obtained results were compared with GSA in terms of average best fitness and computational time. The success of the electrification of transportation sector solely depends on charging infrastructure. Only proper charging control and infrastructure management can assure the larger penetration of PHEVs. The researchers should try to develop efficient control mechanism for charging infrastructure in order to facilitate upcoming PHEVs in highways. In future, more vehicles should be considered for intelligent power allocation strategy as well as other hybrid versions of computational techniques should be applied to ensure higher fitness value and low computational time.

## ACKNOWLEDGMENT

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

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## KEY TERMS AND DEFINITIONS

**All Electric Range:** All electric range is a mode of electric vehicle when it is only run by charged batteries in order to reduce the overall fuel consumption. Calculation of all electric range varies according to the designs of the hybrid electric vehicles. The "all electric range" (AER) test quantifies the electric-only miles possible with the battery for a particular configuration and vehicle class.

**Charging Station:** Charging station is an important component for the healthy growth of the electric vehicle industry. Charging station refers to an infrastructure similar to petrol station (for conventional vehicle) that provides electric energy for the charging of plug-in hybrid electric vehicles (PHEVs). Many charging stations are on-street facilities provided by electric utility companies, mobile charging stations have been recently introduced. From the grid standpoint, a charging station is one way that the operator of an electrical power grid can adapt energy production to energy consumption, both of which can vary randomly over time. Basically, EVs in a charging station are charged during times when production exceeds consumption and are discharged at times when consumption exceeds production. In this way, electricity production need is not drastically scaled up and down to meet momentary consumption, which would increase efficiency and lower the cost of energy production and facilitate the use of intermittent energy sources, such as photovoltaic and wind.

**Energy Security:** The interest in energy security is based on the notion that an uninterrupted supply of energy is critical for the functioning of an economy. However, an exact definition of energy security is hard to give as it has different meanings to different people at different moments in time. It has traditionally been associated with the securing of access to oil supplies and with impending fossil fuel depletion. With an increase in natural gas use, security concerns also arose for natural gas, widening the concept to cover other fuels. Because oil is nowadays a globally traded commodity, physical shortages show up in the price of oil on the world market, in the form of a long-term increase and of short-term fluctuations.

**Fitness Function:** A necessary characteristic of evolutionary structural testing is that the fitness function is constructed on the basis of the software under test. The fitness function itself is not of interest for the problem; however, a well-constructed fitness function may substantially increase the chance of finding a solution and reaching higher coverage. Better guidance of the search can result in optimizations with less iterations, therefore leading to savings in resource expenditure.

**Gravitational Search Algorithm:** Gravitational Search Algorithm (GSA) is a heuristic optimization algorithm which has been gaining much interest among the scientific community recently. GSA is a nature inspired algorithm based on the Newton's famous law of gravity and the law of motion. GSA is classified under population-based method and is reported to be more instinctive. In GSA, the agent has four parameters which are position, inertial mass, active gravitational mass, and passive gravitational mass. GSA is a memory-less algorithm. However, it works efficiently like the algorithms with memory.

**Particle Swarm Optimization:** Particle Swarm Optimization (PSO) algorithm was introduced by Kennedy and Eberhart in 1995, which is a heuristic global optimization method and a member of swarm intelligence family. PSO is a computational intelligence-based technique that is not largely affected by the size and nonlinearity of the problem, and can converge to the optimal solution in many problems where most analytical methods fail to converge.

**Plug-in Hybrid Electric Vehicles:** Plug-in Hybrid Electric Vehicles (PHEVs) are being made with relatively large sized batteries that can be charged during off-peak hours, and permit the vehicle owner to use exclusively electric made for 30 – 60 miles of driving as well as switching into traditional gasoline for longer trips. PHEVs offer customers the opportunity for fuel at gasoline-equivalent prices of less than $1.00 per gallon. For a given size battery bank, the range of a PHEV can be prolonged significantly before batteries need recharging by turning on the engine or fuel cell whenever the vehicle power demand exceeds some threshold.

**Smart Charging:** Smart charging refers to the intelligent control of electric vehicle charging by the assigned authority. Smart charging can be both direct and indirect depending upon the user demand and available infrastructure. The main concept of smart charging lies in the charging of vehicle when the price and demand are lowest as well as excess amount of available capacity.

**Smart Grid:** Smart grid is an intelligent bi-directional electrical power system. It ensures most advanced and efficient communication network between suppliers and consumers of electricity. Unlike traditional power grid, smart grid offers better system sustainability and network security. The "smart grid" includes advanced utility Supervisory Control and Data Acquisition (SCADA) systems that can keep track of thousands of data points of loads and resources, smart meters that can communicate to the utility SCADA center, and smart appliances that can respond instantaneously to economic or reliability imperatives.

**State-of-Charge:** State-of-Charge (SoC) of a PHEV battery is expressed as the ratio of its capacity of current $\mathrm{Q}(t)$ to the nominal capacity $Q_n$. The nominal capacity is known by the vehicle manufacturer and shows the maximum amount of charge that can be stored in the battery. SoC estimation is a fundamental challenge for battery use. The SoC of a battery, which is used to describe its remaining capacity, is a very important parameter for a control strategy. The SoC can be defined as follows: $SoC = {}^{Q(t)}\!/_{Q_n}$.

**Vehicle-to-Grid:** In vehicle-to-grid (V2G) concept, an electric vehicle acts both as a load and power source in smart grid environment. A V2G-capable vehicle offers reactive power support, active power regulation, tracking of variable renewable energy sources, load balancing, and current harmonic filtering. These technologies can enable ancillary services, such as voltage and frequency control and spinning reserve. Success of the V2G concept depends on standardization of requirements and infrastructure decisions, battery technology, and efficient and smart scheduling of limited fast-charge infrastructure.

## APPENDIX: 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.
$\mathrm{I}_{\mathrm{i}}\left(k\right)$**:** Charging current over $\Delta t$.
$V_{i}\left(k\right)$**:** Charging voltage over $\Delta t$.
$C_{r,i}\left(k\right)$**:** 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).
$T_{r,i}\left(k\right)$**:** Remaining time for charging the i-th PHEV at time step k.
$D_{i}\left(k\right)$**:** Price difference.
$w_{i}\left(k\right)$**:** Charging weighting term of the i-th PHEV at time step k.
$SoC_{i}\left(k+1\right)$**:** State-of-charge of the i-th PHEV at time step k+1.
$SoC_{i,\max}$**:** User-defined maximum battery $\mathrm{SoC}$ limit for the i-th PHEV.
**J (k):** Fitness function.
$P_{utility}$**:** Power available from the utility.
$P_{i,\max}$**:** Maximum power that can be absorbed by a specific PHEV.
$\eta$**:** Overall charging efficiency of the charging station.
$\Delta t$**:** Total charging time.
**PSO:** Particle swarm optimization.
**GSA:** Gravitational search algorithm.
**PSOGSA:** (Hybrid) Particle swarm optimization and Gravitational search algorithm.
**EMS:** Energy management strategy.
**EVSE:** Electric vehicle supply equipment.
**DG:** Distributed generation.
**DSM:** Demand side management.
**SMDP:** Stochastic semi-Markov decision.