Handbook of Research on Swarm Intelligence in Engineering

Siddhartha Bhattacharyya
RCC Institute of Information Technology, India

Paramartha Dutta
Visva-Bharati University, India

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

ENGINEERING SCIENCE REFERENCE
An Imprint of IGI Global

Managing Director: Lindsay Johnston
Managing Editor: Austin DeMarco
Director of Intellectual Property & Contracts: Jan Travers
Acquisitions Editor: Kayla Wolfe
Production Editor: Christina Henning
Development Editor: Caitlyn Martin
Typesetter: Kaitlyn Kulp
Cover Design: Jason Mull

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

Handbook of research on swarm intelligence in engineering / Siddhartha Bhattacharyya and Paramartha Dutta, editors.
pages cm
Includes bibliographical references and index.
ISBN 978-1-4666-8291-7 (hardcover) -- ISBN 978-1-4666-8292-4 (ebook) 1. Swarm intelligence. I. Bhattacharyya, Siddhartha, 1975- editor. II. Dutta, Paramartha, editor.
Q337.3.H36 2015
620.00285'63824--dc23
2015003786

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.

All work contributed to this book is new, previously-unpublished material. The views expressed in this book are those of the authors, but not necessarily of the publisher.

For electronic access to this publication, please contact: eresources@igi-global.com.

Chapter 12
Swarm Intelligence-Based Optimization for PHEV Charging Stations

Imran Rahman
Universiti Teknologi Petronas, Malaysia

Pandian Vasant
Universiti Teknologi Petronas, Malaysia

Balbir Singh Mahinder Singh
Universiti Teknologi Petronas, Malaysia

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

ABSTRACT

In this chapter, Gravitational Search Algorithm (GSA) and Particle Swarm Optimization (PSO) technique were applied for intelligent allocation of energy to the Plug-in Hybrid Electric Vehicles (PHEVs). Considering constraints such as energy price, remaining battery capacity, and remaining charging time, they optimized the State-of-Charge (SoC), a key performance indicator in hybrid electric vehicle for the betterment of charging infrastructure. Simulation results obtained for maximizing the highly non-linear objective function evaluates the performance of both techniques in terms of global best fitness 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 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

DOI: 10.4018/978-1-4666-8291-7.ch012

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 a statistics of Electric Power Research Institute (EPRI), about 62% of the entire United States (US) vehicle will comprise of PHEVs within the year 2050 (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 vehicles, 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, 2012b). 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.

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).

PSO is based on two fundamental disciplines: social science and computer science. In addition, PSO uses the swarm intelligence concept, which is the property of a system, whereby the collective behaviors of unsophisticated agents that are interacting locally with their environment create coherent global functional patterns. PSO algorithm has been successfully used for solving many problems related to power systems (Venayagamoorthy, G. K., Mohagheghi,2008) such as voltage security, optimal power flow, power system operation and planning, dynamic security, power quality, unit commitment, reactive power control, capacitor placement and optimizing controller parameters.

Moreover, 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).

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). It is expected that mostly recharging will occur at home even if there is a sufficient public charging station network. It does not necessarily mean that there is no or lower need of public charging stations because many residences do not have adequate facilities for recharging EVs (Ul-Haq, Buccella, Cecati, & Khalid, 2013). 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. Two swarm intelligence-based methods, Particle swarm optimization (PSO) and Gravitational search algorithm (GSA) were applied for solving the optimization problem.

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 vehicle 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)

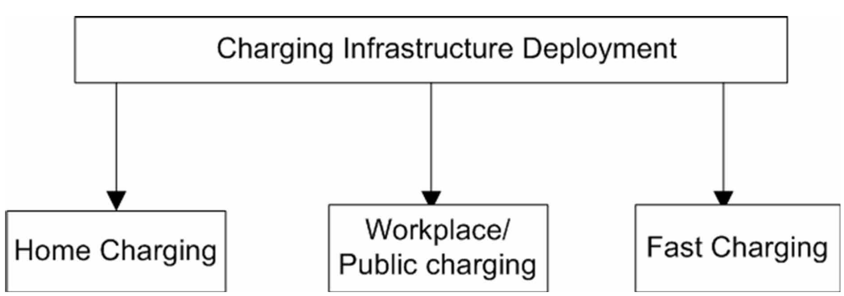
Level-3 (DC fast charging) can be installed in highways and urban refueling points which is similar to petrol stations. It generally operates with a 480 V or higher three phase circuit and needs an off-board charger to provide regulated ac-dc conversion. Level-3 charging is very rear in the residential premises. Standards for dc plugs and hardware are in progress. CHAdeMO-a Japanese protocol is gaining world-wide 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. Charging 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.

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

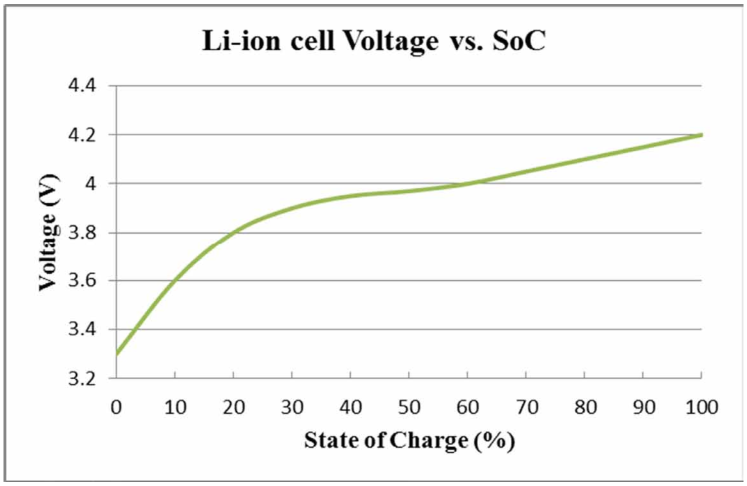
Problem Statement

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, 2012a). 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 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

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



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 objective 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 (Su & Chow, 2012b).

The objective function is defined as:

$$\text{üüü}\;\; J\left(k\right)\;\; \sum_{i} w_i\left(k\right) SoC_i\left(k+\;\right) \tag{1}$$

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

$$\text{üüü}_{r,i}\left(\;\;\right)=\left(1-\qquad {}_i\left(\;\;\right)\right)\cdot\quad {}_i \tag{3}$$

where $C_{r,i}(k)$ is the battery capacity (remaining) needed to be filled for *i* no. of PHEV at time step *k*; C_i is the battery capacity (rated) of the *i* no. of PHEV; remaining time for charging a particular PHEV at time step *k* is expressed as $T_{r,i}(k)$; the price difference between the real-time energy price and the price that a specific customer at the *i* no. of PHEV charger is willing to pay at time step *k* is presented by $D_i(k)$; $w_i(k)$ is the charging weighting term of the *i* no. of PHEV at time step *k* (a function of charging time, present SoC and price of the energy); $SoC_i(k+1)$ is the state of charge of the *i* no. of PHEV at time step $k+1$.

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

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

The charging current is also assumed to be constant over Δt.

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

$$SoC_i(k+1) = SoC_i(k) + \mathrm{I}_\mathrm{i}(k)\Delta t \,/\, Cap_i \tag{6}$$

where the sample time Δt is defined by the charging station operators, and $\mathrm{I}_\mathrm{i}(k)$ is the charging current over Δt.

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

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

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

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

$$\text{®}_1(\text{®®}+1) - \quad {}_i(\quad) = {}_i\Delta \quad / \quad {}_i \tag{9}$$

As the decision variable used here is the allocated power to the PHEVs, by replacing $\mathrm{I}_\mathrm{i}(k)$ with $P_i(k)$ the objective function finally becomes:

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

Possible real-world constraints could include the charging rate (i.e., slow, medium, and fast), the time that the PHEV is connected to the grid, the desired departure state-of-charge, the maximum electricity price that a user is willing to pay, certain battery requirements etc. Furthermore, the available communication bandwidth could limit sampling time, which would have effects on the processing ability of the vehicle.

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

Table 1 shows all the objective 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).

Table 1. Parameter settings of the objective function

Parameter	Values
Fixed Parameters	Maximum power, $P_{i,max}$ = 6.7 kWh
	Charging station efficiency, η = 0.9
	Total charging time, Δt = 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	$\sum_i P_i(k) \le P_{utility}(k) \times \eta$
	$0 \le P_i(k) \le P_{i,\max}(k)$
	$0 \le$ üüüü$_i(\quad) \le \quad_{i,\max}$
	$0 \le SoC_i(k+1) - SoC_i(k) \le \Delta SoC_{\max}$

PROPOSED METHODS

Particle Swarm Optimization

PSO is an evolutionary computation technique which is proposed by Eberhart and Yuhui (2001). The PSO is inspired from social behavior of bird flocking. It uses a number of particles (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 has found so far.

A PSO system begins with a primary initial population of random individuals, signifies solutions of problem, to which are allocated random velocities. Each particle in PSO should consider the current position, the current velocity, the distance to *pbest*, and the distance to *gbest* to modify its position. PSO is an iterative stochastic optimization method. It simulates the behavior of flocks of birds or schools of fish. In PSO, each solution is a "bird" (or, more generally, a "particle") in the search space. All of the particles have (1) fitness values (which are evaluated by the fitness function to be optimized) and (2) velocities (which direct the flying of the particles). The particles fly through the search space by following the current optimum particles. At each iteration, each of the particles is updated by following the individual and group bests. Gradually, the particles tend toward the global "near-optima" region.

PSO was mathematically modeled as followed as:

$$V_i^{t+1} = wv_i^t + c_1 . \ rand \ . \left(pbest_i - x_i^t\right) + c_2 . rand . \left(gbest - x_i^t\right) \tag{11}$$

$$x_i^{t+1} = x_i^t + V_i^{t+1} \tag{12}$$

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

$$\omega = \omega_{\max} - \frac{w_{\max} - \omega_{\min}}{Itre_{\max}} \ Itre \tag{13}$$

Appropriate values for ω_{min} and ω_{max} are 0.4 and 0.9. Appropriate value ranges for c_1 and c_2 are 1 to 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. The parameter settings for PSO are demonstrated in Table 2. Total size of the swarm is 100 and PSO inertia is taken as 0.9. PSO is also fairly immune to the size and non-linear nature of the objective function being considered. The algorithm does not converge with less iterations, while more iterations increase computation complexity, so the maximum iterations are 100. Moreover, from the previous literature experiences, maximum 100 iterations are suitable for the PSO-based optimization.

The main advantage of PSO is its simplicity, while being capable of delivering accurate results consistently. It is fast and also very flexible, being applicable to a wide range of problems, with limited computational requirements (Eberhart & Yuhui, 2001). For these reasons, the present work focuses on

Table 2. PSO parameter settings

Parameters	Values
Size of the swarm	100
Maximum no. of steps	100
PSO parameter,c1	1.4
PSO parameter,c2	1.4
PSO inertia (w)	0.9
Maximum iteration	100
Number of runs	50

meta-heuristics optimization approaches, namely PSO applied in order to optimize the State-of-Charge for Charging Plug-in Hybrid Electric Vehicles.

Figure 3 shows the Structural diagram for PSO algorithm. 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 (*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).

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.

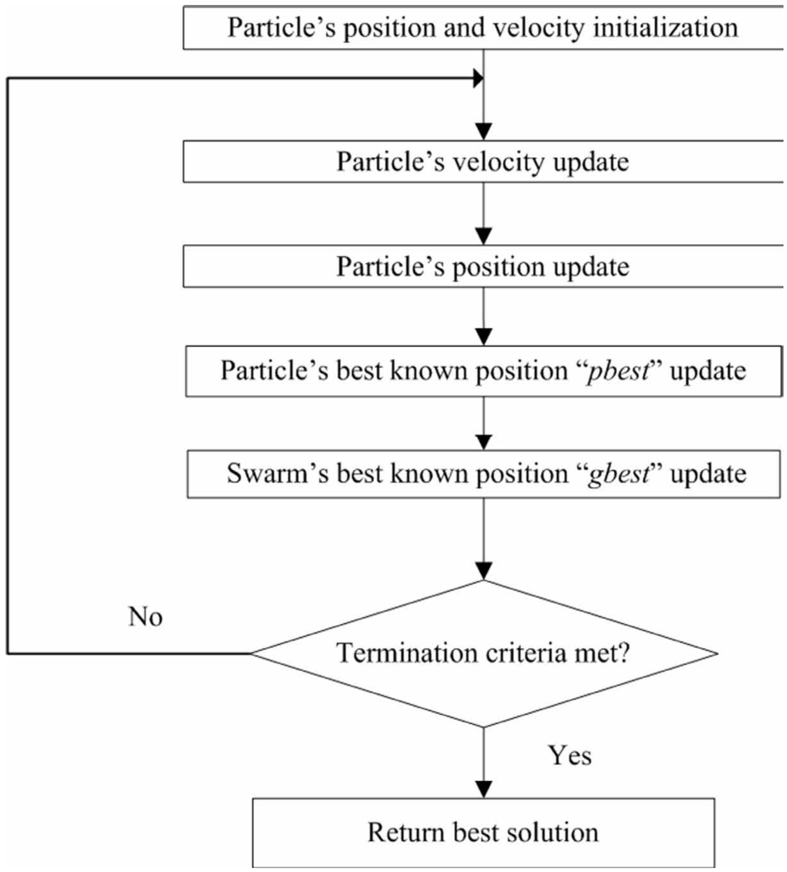
Law of Gravity: The law states that particles attract each other and the force of gravitation between two particles is directly proportional to the product of their masses and inversely proportional to the distance between them.

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:

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

Figure 3. Structural diagram of Particle Swarm Optimization



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*, ε is a small constant and $R_{ij}(t)$ is the Euclidian distance between two agents *i* and *j*. The G(t) is calculated as-

$$G(t) = G_0 \times \exp(-\alpha.iter / \max iter) \tag{15}$$

where α 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:

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

where $rand_j$ 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:

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

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

$$vel_i^d\left(t+1\right)=rand_i.vel_i^d\left(t\right)+ac_i^d\left(t\right) \tag{18}$$

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

where $rand_i$ is a random number with interval [0, 1].

Gravitational and inertia masses are simply calculated by the fitness evaluation. A heavier mass means a more efficient agent. This means that better agents have higher attractions and walk more slowly. Assuming the equality of the gravitational and inertia mass, the values of masses are calculated using the map of fitness. We update the gravitational and inertial masses by the following equations:

$$M_{ai}=M_{pi}=M_{ii}=M_i, i=1,2,\ldots,N \tag{20}$$

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 3. The GSA parameters were selected: Primary parameter, G_0 = 100, Acceleration coefficient, α =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 3. GSA parameter settings

Parameters	Values
Primary parameter, G_0	100
No. of mass agents, n	100
Acceleration coefficient, α	20
Constant parameter	.01
Power of ‘R’	1
Maximum iteration	100
Number of runs	50

The Algorithm Outline

The outline of gravitational search algorithm is given in Algorithm 1.

Moreover, the step involves in optimization using GSA is shown Figure 4. 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, Kelly, Resende, & Stewart Jr, 1995). In GSA, the stable convergence and better exploitation rate ensures good quality solution, which is expressed in terms of best fitness function.

Solutions and Recommendations

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

Figure 5 shows 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.

Algorithm 1.

```
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.              Fitness_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
         Then return Best Fitness solution so far
         Else
                 Modification of solution
                                     }
4.        Failed to meet stopping criteria,
           Go To Step 2, Else Stop
```

Figure 4. Structural diagram of Gravitational Search Algorithm

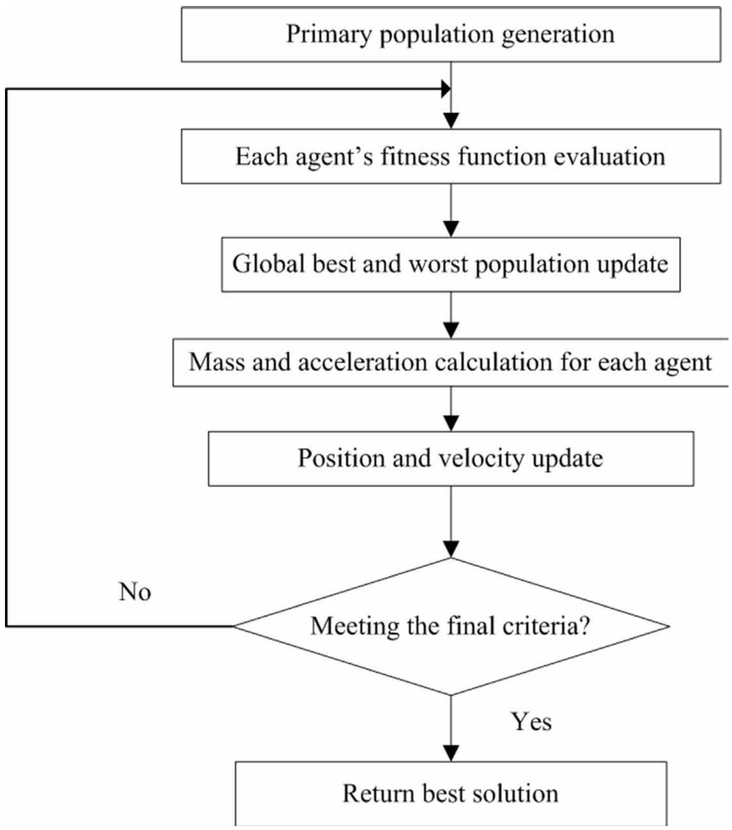
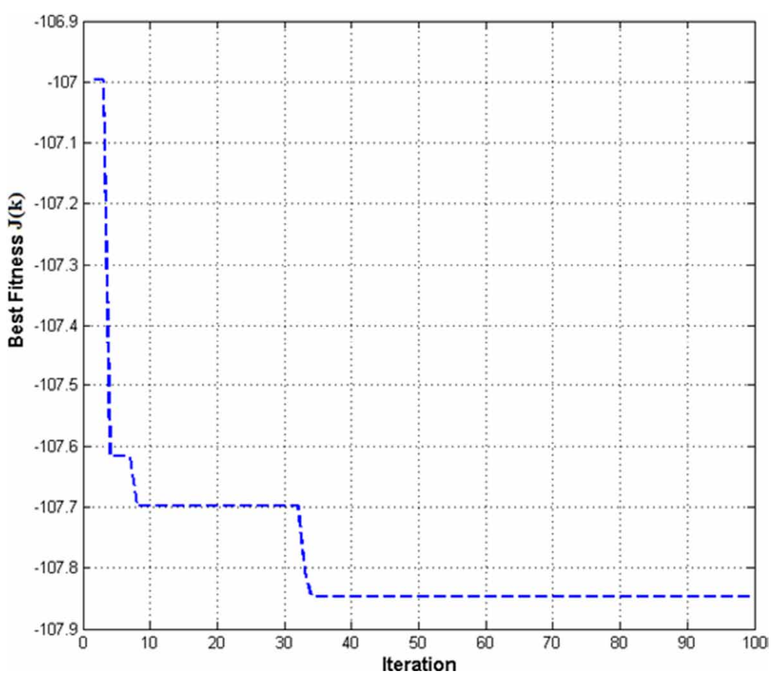


Figure 5. Iteration vs. fitness value, J (k) for GSA [100 PHEVs]



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.

Particle Swarm Optimization (PSO) with the parameter settings stated in Table 2 was also performed for the same objective 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 w were set as standard values, 1.4, 1.4 and 0.9 respectively. It can be apparently seen from Figure 6 that although the algorithm has been set to run for maximum 100 iterations, but the convergence happened in about 10 iterations. So, PSO takes less iterations to converge than GSA method due to the weak local search ability of GSA.

Comparison between GSA and PSO

Table 4 summarizes the comparisons of GSA with PSO 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 PSO, 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 PSO 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. PSO can easily handle the constraints separately, eliminating the need for additional parameters (Su & Chow, 2012a). PSO method is good for multi-

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

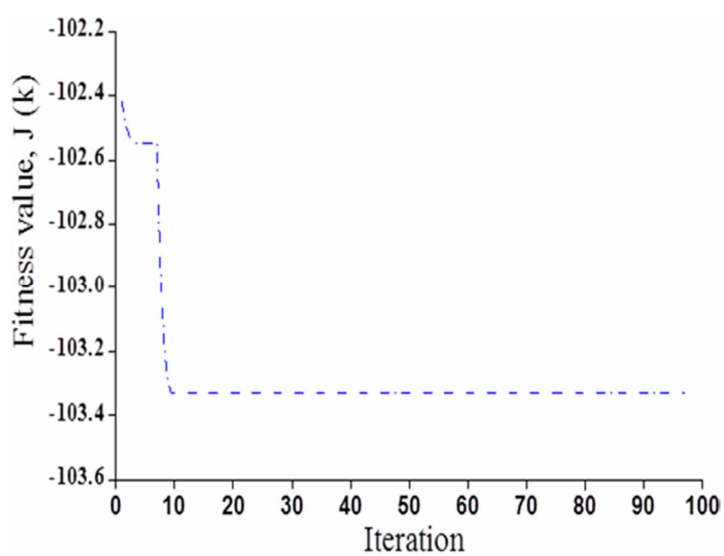


Table 4. Average best fitness comparison between GSA and PSO

Average Best Fitness for	PSO	GSA
50 PHEVs	142.839	158.8289
100 PHEVs	171.102	182.3097
500 PHEVs	150.869	152.36437
1000 PHEVs	156.802	161.52349

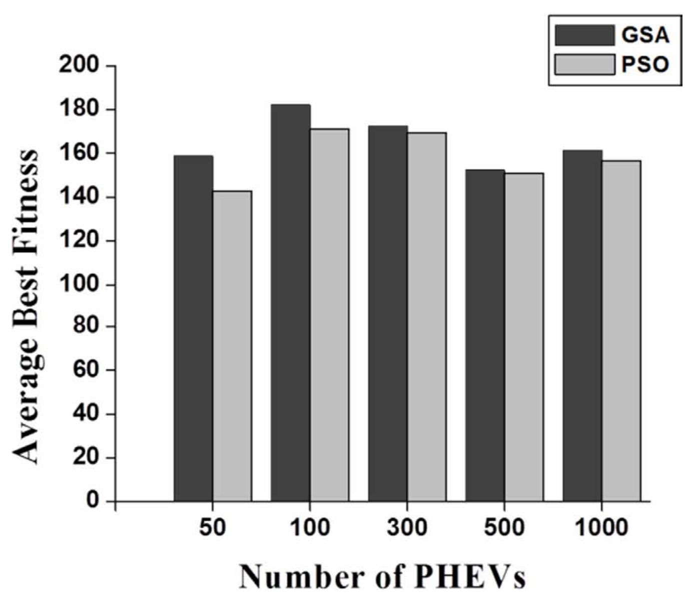
Table 5. Advantages and disadvantages of PSO and GSA

Optimization Method	Advantages	Disadvantages
PSO	Less parameters tuning Easy constraint Good for multi-objective optimization	Low quality solution Needs memory to update velocity Slow convergence rate
GSA	High quality solution Good convergence rate Local exploitation capability	Needs more Computational time More parameters tuning

objective optimization while GSA takes slightly more computational time with parameters tuning. The performance of both algorithms varies with the applications and different objective functions.

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, Gravitational Search Algorithm (GSA) outperforms Particle Swarm Optimization (PSO) 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 GSA is good through the fast information flowing among mass agents, so its diversity decreases very quickly

Figure 7. Average best fitness vs. no. of PHEVs



in the successive iterations and lead to a suboptimal solution. Starting from 50 numbers of PHEVs up to 1000 PHEVs, GSA shows better fitness value than PSO.

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

Stability

Here, the average best fitness gives different values with the increment of PHEVs population. The rate of convergence of mass agents in GSA is good through the fast information flowing among mass agents, so its stability decreases very quickly in the successive iterations and lead to a suboptimal solution.

Robustness

The similar numeric patterns of Average best fitness shows the robustness of GSA method. This method resists change without adapting its initial stable configuration for different cases (no. of PHEVs) which proves GSA as a robust algorithm.

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

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:

- Optimization techniques like evolutionary algorithms, direct search methods 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.

Table 6. Computational time for PSO and GSA

Computational Time (sec.)	PSO	GSA
50 PHEVs	1.650	2.721
100 PHEVs	1.686	4.439
500 PHEVs	1.990	18.165
1000 PHEVs	2.398	36.275

- 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.
- 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.
- The future optimization tools should have the capability of stable convergence and thus provides good solution to the desired objective functions.
- Exploration and exploitation of the search space is essential in order to get desired solution within acceptable computation time.
- 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

Considering the effects of cost and performance on the marketability of PHEVs, the objective 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 objective 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 objective 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, Particle swarm optimization (PSO) and Gravitational search algorithm (GSA)-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 PSO 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 hybrid versions of PSO and GSA 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.

REFERENCES

Aggeler, D., Canales, F., Coccia, A., Butcher, N., & Apeldoorn, O. (2010). Ultra-fast DC-charge infrastructures for EV-mobility and future smart grids. In Proceedings of Innovative Smart Grid Technologies Conference Europe (ISGT Europe). Gothenburg, Sweden: IEEE. doi:10.1109/ISGTEUROPE.2010.5638899

Anegawa, T. (2009). *Desirable characteristics of public quick charger*. Retrieved December, 1, 2011 from www.chademo.com

Association of Bay Area Governments. (2010). *Bay area electrified vehicle charging infrastructure: Options for accelerating consumer*. Bay Area, CA: Renewable and Appropriate Energy Laboratory.

Barr, R. S., Golden, B. L., Kelly, J. P., Resende, M. G., & Stewart, W. R. Jr. (1995). Designing and reporting on computational experiments with heuristic methods. *Journal of Heuristics*, *1*(1), 9–32. doi:10.1007/BF02430363

Birnie, D. P. III. (2009). Solar-to-vehicle (S2V) systems for powering commuters of the future. *Journal of Power Sources*, *186*(2), 539–542. doi:10.1016/j.jpowsour.2008.09.118

Botsford, C., & Szczepanek, A. (2009). Fast charging vs. slow charging: Pros and cons for the new age of electric vehicles. In *Proceedings of International Battery Hybrid Fuel Cell Electric Vehicle Symposium*. Stavanger, Norway: World Electric Vehicle Association.

Boyle, G. (Ed.). (2007). *Renewable electricity and the grid: the challenge of variability*. Earthscan.

Caramanis, M., & Foster, J. M. (2009, December). Management of electric vehicle charging to mitigate renewable generation intermittency and distribution network congestion. In *Proceedings of the 48th IEEE Conference on Decision and Control*. Shanghai: IEEE. doi:10.1109/CDC.2009.5399955

Chang, W. Y. (2013). The state of charge estimating methods for battery: A review. *ISRN Applied Mathematics*, 2013.

Chiasson, J., & Vairamohan, B. (2005). Estimating the state of charge of a battery. *IEEE Transactions on Control Systems Technology*, *13*(3), 465–470. doi:10.1109/TCST.2004.839571

De Sousa, L., Silvestre, B., & Bouchez, B. (2010). A combined multiphase electric drive and fast battery charger for electric vehicles. In *Proceedings of Vehicle Power and Propulsion Conference (VPPC)*. Lille, France: IEEE. doi:10.1109/VPPC.2010.5729057

del Valle, Y., Venayagamoorthy, G. K., Mohagheghi, S., Hernandez, J.-C., & Harley, R. G. (2008). Particle swarm optimization: Basic concepts, variants and applications in power systems. *IEEE Transactions on Evolutionary Computation*, *12*(2), 171–195. doi:10.1109/TEVC.2007.896686

Denholm, P., Kuss, M., & Margolis, R. M. (2013). Co-benefits of large scale plug-in hybrid electric vehicle and solar PV deployment. *Journal of Power Sources*, *236*, 350–356. doi:10.1016/j.jpowsour.2012.10.007

Dubey, H. M., Pandit, M., Panigrahi, B. K., & Udgir, M. (2013). Economic load dispatch by hybrid swarm intelligence based gravitational search algorithm. *International Journal of Intelligent Systems and Applications*, *5*(8), 21–32. doi:10.5815/ijisa.2013.08.03

Dusmez, S., Cook, A., & Khaligh, A. (2011). Comprehensive analysis of high quality power converters for level 3 off-board chargers. In *Proceedings of Vehicle Power and Propulsion Conference (VPPC)*. Chicago: IEEE doi:10.1109/VPPC.2011.6043096

Eberhart, R. C., & Shi, Y. (2001). Particle swarm optimization: Developments, applications and resources. In *Proceedings of the 2001 Congress on Evolutionary Computation*. Seoul, South Korea: IEEE. doi:10.1109/CEC.2001.934374

Gan, L., Topcu, U., & Low, S. (2011). Optimal decentralized protocol for electric vehicle charging. In *Proceedings of Decision and Control and European Control Conference (CDC-ECC)*. IEEE. doi:10.1109/CDC.2011.6161220

Ganesan, T., Vasant, P., & Elamvazuthy, I. (2012). A hybrid PSO approach for solving non-convex optimization problems. *Archives of Control Sciences*, *22*(1), 87–105. doi:10.2478/v10170-011-0014-2

Gerkensmeyer, C., Kintner-Meyer, M. C., & DeSteese, J. G. (2010). *Technical challenges of plug-in hybrid electric vehicles and impacts to the US power system: Distribution system analysis*. United States Department of Energy. doi:10.2172/974954

Hess, A., Malandrino, F., Reinhardt, M. B., Casetti, C., Hummel, K. A., & Barceló-Ordinas, J. M. (2012). Optimal deployment of charging stations for electric vehicular networks. In *Proceedings of the First Workshop on Urban Networking*. Nice, France: ACM. doi:10.1145/2413236.2413238

Holtz-Eakin, D., & Selden, T. M. (1995). Stoking the fires? CO_2 emissions and economic growth. *Journal of Public Economics*, *57*(1), 85–101. doi:10.1016/0047-2727(94)01449-X

Hota, A. R., Juvvanapudi, M., & Bajpai, P. (2014). Issues and solution approaches in PHEV integration to the smart grid. *Renewable & Sustainable Energy Reviews*, *30*(0), 217–229. doi:10.1016/j.rser.2013.10.008

Ingersoll, J. G., & Perkins, C. A. (1996). The 2.1 kW photovoltaic electric vehicle charging station in the city of Santa Monica, California. In *Proceedings of Twenty Fifth IEEE Photovoltaic Specialists Conference*. Washington, DC: IEEE. doi:10.1109/PVSC.1996.564423

Jia-zhao, C., Yu-xiang, Z., & Yin-sheng, L. (2012). A unified frame of swarm intelligence optimization algorithm. *Knowledge Discovery and Data Mining*, *135*, 745–751. doi:10.1007/978-3-642-27708-5_103

Kefayati, M., & Caramanis, C. (2010). Efficient energy delivery management for PHEVs. In *Proceedings of First IEEE International Conference on Smart Grid Communications (SmartGridComm)*. Gaithersburg, MD: IEEE. doi:10.1109/SMARTGRID.2010.5621990

Kulshrestha, P., Wang, L., Chow, M. Y., & Lukic, S. (2009). Intelligent energy management system simulator for PHEVs at municipal parking deck in a smart grid environment. In Proceedings of Power & Energy Society General Meeting. Alberta, Canada: IEEE. doi:10.1109/PES.2009.5275688

Letendre, S. (2009). Solar electricity as a fuel for light vehicles. In *Proceedings of the 2006 American Solar Energy Society Annual Conference*. Boulder, CO: ASES.

Li, Z., Sahinoglu, Z., Tao, Z., & Teo, K. H. (2010, September). Electric vehicles network with nomadic portable charging stations. In Proceedings of Vehicular Technology Conference Fall. Ottawa, Canada: IEEE. doi:10.1109/VETECF.2010.5594437

Lund, H., & Kempton, W. (2008). Integration of renewable energy into the transport and electricity sectors through V2G. *Energy Policy*, *36*(9), 3578–3587. doi:10.1016/j.enpol.2008.06.007

Ma, Z., Callaway, D., & Hiskens, I. (2010). Decentralized charging control for large populations of plug-in electric vehicles. In *Proceedings of 49th IEEE Conference on Decision and Control (CDC)*. Yokohama: IEEE. doi:10.1109/CDC.2010.5717547

Mayfield, D. (2012). *Site design for electric vehicle charging stations, NREL*. US Department of Energy.

Mitra, P., & Venayagamoorthy, G. K. (2010). Intelligent coordinated control of a wind farm and distributed smartparks. In *Proceedings of Industry Applications Society Annual Meeting (IAS)*. Houston, TX: IEEE. doi:10.1109/IAS.2010.5615930

Morrow, K., Karner, D., & Francfort, J. (2008). *Plug-in hybrid electric vehicle charging infrastructure review*. US Department of Energy-Vehicle Technologies Program.

Motors, T. (2009). Tesla roadster spec sheet 2009. *USA Today*. Retrieved from www.usatoday.com

Neumann, H. M., Schär, D., & Baumgartner, F. (2012). The potential of photovoltaic carports to cover the energy demand of road passenger transport. *Progress in Photovoltaics: Research and Applications*, *20*(6), 639–649.

Pang, C., Dutta, P., Kim, S., Kezunovic, M., & Damnjanovic, I. (2010). PHEVs as dynamically configurable dispersed energy storage for V2B uses in the smart grid. In *IET Conference Proceedings*. Cyprus: IEEE. doi:10.1049/cp.2010.0903

Piller, S., Perrin, M., & Jossen, A. (2001). Methods for state-of-charge determination and their applications. *Journal of Power Sources*, *96*(1), 113–120. doi:10.1016/S0378-7753(01)00560-2

Rashedi, E., Nezamabadi-Pour, H., & Saryazdi, S. (2009). GSA: A gravitational search algorithm. *Information Sciences*, *179*(13), 2232–2248. doi:10.1016/j.ins.2009.03.004

Rawson, M., & Kateley, S. (1999). *Electric vehicle charging equipment design and health and safety codes* (No. 1999-01-2941). SAE Technical Paper.

Sabri, N. M., Puteh, M., & Mahmood, M. R. (2013). A review of gravitational search algorithm. *Int. J. Advance. Soft Comput. Appl*, *5*(3), 1–39.

Shafiei, A., & Williamson, S. S. (2010). Plug-in hybrid electric vehicle charging: Current issues and future challenges. In *Proceedings of Vehicle Power and Propulsion Conference (VPPC)*. Lille, France: IEEE. doi:10.1109/VPPC.2010.5729134

Soares, J., Sousa, T., Morais, H., Vale, Z., Canizes, B., & Silva, A. (2013). Application-specific modified particle swarm optimization for energy resource scheduling considering vehicle-to-grid. *Applied Soft Computing*, *13*(11), 4264–4280. doi:10.1016/j.asoc.2013.07.003

Sojoudi, S., & Low, S. H. (2011). Optimal charging of plug-in hybrid electric vehicles in smart grids. In *Proceedings of Power and Energy Society General Meeting.* San Diego, CA: IEEE. doi:10.1109/PES.2011.6039236

Su, W., & Chow, M. Y. (2010). An intelligent energy management system for PHEVs considering demand response. In *Proceedings of FREEDM Annual Conference*. NC State University.

Su, W., & Chow, M. Y. (2011). Performance evaluation of a PHEV parking station using particle swarm optimization. In *Proceedings of Power and Energy Society General Meeting.* San Diego, CA: IEEE. doi:10.1109/PES.2011.6038937

Su, W., & Chow, M.-Y. (2012a). Performance evaluation of an EDA-based large-scale plug-in hybrid electric vehicle charging algorithm. *IEEE Transactions on Smart Grid*, *3*(1), 308–315. doi:10.1109/TSG.2011.2151888

Su, W., & Chow, M.-Y. (2012b). Computational intelligence-based energy management for a large-scale PHEV/PEV enabled municipal parking deck. *Applied Energy*, *96*, 171–182. doi:10.1016/j.apenergy.2011.11.088

Subramanian, A., Garcia, M., Dominguez-Garcia, A., Callaway, D., Poolla, K., & Varaiya, P. (2012). Real-time scheduling of deferrable electric loads. In *Proceedings of American Control Conference (ACC)*. Montreal, Canada: IEEE. doi:10.1109/ACC.2012.6315670

Tan, W. S., Hassan, M. Y., Rahman, H. A., Abdullah, M. P., & Hussin, F. (2013). Multi-distributed generation planning using hybrid particle swarm optimisation-gravitational search algorithm including voltage rise issue. *IET Generation, Transmission, & Distribution*, *7*(9), 929–942. doi:10.1049/iet-gtd.2013.0050

Tie, S. F., & Tan, C. W. (2013). A review of energy sources and energy management system in electric vehicles. *Renewable & Sustainable Energy Reviews*, *20*, 82–102. doi:10.1016/j.rser.2012.11.077

Tulpule, P. J., Marano, V., Yurkovich, S., & Rizzoni, G. (2013). Economic and environmental impacts of a PV powered workplace parking garage charging station. *Applied Energy*, *108*, 323–332. doi:10.1016/j.apenergy.2013.02.068

Ul-Haq, A., Buccella, C., Cecati, C., & Khalid, H. A. (2013). Smart charging infrastructure for electric vehicles. In *Proceedings of International Conference on Clean Electrical Power (ICCEP)*. Alghero: IEEE. doi:10.1109/ICCEP.2013.6586984

Vasant, P., Ganesan, T., & Elamvazuthi, I. (2012). An improved PSO approach for solving non-convex optimization problems. In *Proceedings of Engineering 9th International Conference on ICT and Knowledge*. Bangkok: IEEE. doi:10.1109/ICTKE.2012.6152418

Venayagamoorthy, G. K., & Mitra, P. (2011). SmartPark shock absorbers for wind farms. *IEEE Transactions on Energy Conversion*, *26*(3), 990–992. doi:10.1109/TEC.2011.2159549

Yilmaz, M., & Krein, P. T. (2012). Review of charging power levels and infrastructure for plug-in electric and hybrid vehicles. In *Proceedings of Electric Vehicle Conference (IEVC)*. Greenville, SC: IEEE. doi:10.1109/IEVC.2012.6183208

Zhang, Q., Tezuka, T., Ishihara, K. N., & Mclellan, B. C. (2012). Integration of PV power into future low-carbon smart electricity systems with EV and HP in Kansai Area, Japan. *Renewable Energy*, *44*, 99–108. doi:10.1016/j.renene.2012.01.003

Zhu, L., Yu, F. R., Ning, B., & Tang, T. (2012). Optimal charging control for electric vehicles in smart micro grids with renewable energy sources. In *Proceedings of Vehicular Technology Conference (VTC)*. Yokohama: IEEE.

ADDITIONAL READING

Arumuggam, K., & Singh, B. S. M. (2013). Optimization of hybrid solar and wind power generation. *Journal of Applied Sciences*, *13*(6), 869–875. doi:10.3923/jas.2013.869.875

Axsen, J., & Kurani, K. S. (2013). Hybrid, plug-in hybrid, or electric—What do car buyers want? *Energy Policy*, *61*, 532–543. doi:10.1016/j.enpol.2013.05.122

Bauer, P., Zhou, Y., Doppler, J., & Stembridge, N. (2010, June). Charging of electric vehicles and impact on the grid. In MECHATRONIKA, 13th International Symposium, Teplice (pp. 121-127).

Bayram, I. S., Michailidis, G., Devetsikiotis, M., Granelli, F., & Bhattacharya, S. (2012). *Smart Vehicles in the Smart Grid: Challenges, Trends, and Application to the Design of Charging Stations Control and Optimization Methods for Electric Smart Grids* (pp. 133–145). Springer. doi:10.1007/978-1-4614-1605-0_6

Boschert, S. (20 Talatahari, S., Khalili, E., & Alavizadeh, S. (2013). Accelerated particle swarm for optimum design of frame structures. Mathematical Problems in Engineering, 2013. 06). Plug-in hybrids: The cars that will recharge America: New Society Publishers.

Boulanger, A. G., Chu, A. C., Maxx, S., & Waltz, D. L. (2011). Vehicle electrification: Status and issues. *Proceedings of the IEEE*, *99*(6), 1116–1138. doi:10.1109/JPROC.2011.2112750

Ceylan, O., Ozdemir, A., & Dag, H. (2012). Branch Outage Simulation Based Contingency Screening by Gravitational Search Algorithm. *International Review of Electrical Engineering*, *7*(1).

Chan, C. C. (2002). The state of the art of electric and hybrid vehicles. *Proceedings of the IEEE*, *90*(2), 247–275. doi:10.1109/5.989873

Contestabile, M., Offer, G. J., Slade, R., Jaeger, F., & Thoennes, M. (2011). Battery electric vehicles, hydrogen fuel cells and biofuels. Which will be the winner? *Energy & Environmental Science*, *4*(10), 3754–3772. doi:10.1039/c1ee01804c

Di Silvestre, M. L., Sanseverino, E. R., Zizzo, G., & Graditi, G. (2013). An optimization approach for efficient management of EV parking lots with batteries recharging facilities. *Journal of Ambient Intelligence and Humanized Computing*, *4*(6), 641–649. doi:10.1007/s12652-013-0174-y

Duman, S., Güvenç, U., Sönmez, Y., & Yörükeren, N. (2012). Optimal power flow using gravitational search algorithm. *Energy Conversion and Management*, *59*, 86–95. doi:10.1016/j.enconman.2012.02.024

Duman, S., Güvenç, U., & Yörükeren, N. (2010). Gravitational search algorithm for economic dispatch with valve-point effects. *International Review of Electrical Engineering*, *5*(6), 2890–2895.

Ehsani, M., Gao, Y., & Emadi, A. (2009). *Modern electric, hybrid electric, and fuel cell vehicles: fundamentals, theory, and design*. CRC press.

Eiben, A. E., & Smit, S. K. (2011). Parameter tuning for configuring and analyzing evolutionary algorithms. *Swarm and Evolutionary Computation*, *1*(1), 19–31. doi:10.1016/j.swevo.2011.02.001

Elgammal, A., & Sharaf, A. (2012). Self-regulating particle swarm optimised controller for (photovoltaic-fuel cell) battery charging of hybrid electric vehicles. *Electrical Systems in Transportation, IET*, *2*(2), 77–89. doi:10.1049/iet-est.2011.0021

Fazelpour, F., Vafaeipour, M., Rahbari, O., & Rosen, M. A. (2014). Intelligent optimization to integrate a plug-in hybrid electric vehicle smart parking lot with renewable energy resources and enhance grid characteristics. *Energy Conversion and Management*, *77*, 250–261. doi:10.1016/j.enconman.2013.09.006

Ganesan, T., Elamvazuthi, I., Ku Shaari, K. Z., & Vasant, P. (2013). Swarm intelligence and gravitational search algorithm for multi-objective optimization of synthesis gas production. *Applied Energy*, *103*(0), 368–374. doi:10.1016/j.apenergy.2012.09.059

Ganesan, T., Vasant, P., & Elamvazuthi, I. (2013). Hybrid neuro-swarm optimization approach for design of distributed generation power systems. *Neural Computing & Applications*, *23*(1), 105–117. doi:10.1007/s00521-012-0976-4

Ganesan, T., Vasant, P., & Elamvazuthi, I. (2014). Hopfield neural networks approach for design optimization of hybrid power systems with multiple renewable energy sources in a fuzzy environment. *Journal of Intelligent and Fuzzy Systems*, *26*(5), 2143–2154.

Hamadicharef, B. (2011). Bibliometric analysis of particle swarm optimization (PSO) research 2000-2010. In Artificial Intelligence and Computational Intelligence (pp. 404-411). Springer Berlin Heidelberg.

Hannan, M. A., Azidin, F. A., & Mohamed, A. (2014). Hybrid electric vehicles and their challenges: A review. *Renewable & Sustainable Energy Reviews*, *29*(0), 135–150. doi:10.1016/j.rser.2013.08.097

Hendtlass, T. (2007, September). Fitness estimation and the particle swarm optimisation algorithm. In Evolutionary Computation, 2007. CEC 2007. IEEE Congress on (pp. 4266-4272). IEEE. doi:10.1109/CEC.2007.4425028

Inoa, E., Guo, F., Wang, J., & Choi, W. (2011, May). A full study of a PHEV charging facility based on global optimization and real-time simulation. In Power Electronics and ECCE Asia (ICPE & ECCE), 2011 IEEE 8th International Conference on (pp. 565-570). IEEE. doi:10.1109/ICPE.2011.5944611

Jiang, S., Ji, Z., & Shen, Y. (2014). A novel hybrid particle swarm optimization and gravitational search algorithm for solving economic emission load dispatch problems with various practical constraints. *International Journal of Electrical Power & Energy Systems*, *55*, 628–644. doi:10.1016/j.ijepes.2013.10.006

Karbowski, D., Rousseau, A., Pagerit, S., & Sharer, P. (2006, October). Plug-in vehicle control strategy: from global optimization to real time application. In *22nd Electric Vehicle Symposium, EVS22*, Yokohama, Japan.

Khajehzadeh, M., Taha, M. R., El-Shafie, A., & Eslami, M. (2012). A modified gravitational search algorithm for slope stability analysis. *Engineering Applications of Artificial Intelligence*, *25*(8), 1589–1597. doi:10.1016/j.engappai.2012.01.011

Krause, J., Cordeiro, J., Parpinelli, R. S., & Lopes, H. S. (2013). A survey of swarm algorithms applied to discrete optimization problems. Swarm Intelligence and Bio-inspired Computation: Theory and Applications. Elsevier Science & Technology Books, 169-191.

Martens, D., Baesens, B., & Fawcett, T. (2011). Editorial survey: Swarm intelligence for data mining. *Machine Learning*, *82*(1), 1–42. doi:10.1007/s10994-010-5216-5

Mirjalili, S., Mohd Hashim, S. Z., & Moradian Sardroudi, H. (2012). Training feedforward neural networks using hybrid particle swarm optimization and gravitational search algorithm. *Applied Mathematics and Computation*, *218*(22), 11125–11137. doi:10.1016/j.amc.2012.04.069

Mohamed, A. Z., Lee, S. H., Hsu, H. Y., & Nath, N. (2012). A faster path planner using accelerated particle swarm optimization. *Artificial Life and Robotics*, *17*(2), 233–240. doi:10.1007/s10015-012-0051-3

Mullan, J., Harries, D., Bräunl, T., & Whitely, S. (2012). The technical, economic and commercial viability of the vehicle-to-grid concept. *Energy Policy*, *48*(0), 394–406. doi:10.1016/j.enpol.2012.05.042

Mwasilu, F., Justo, J. J., Kim, E.-K., Do, T. D., & Jung, J.-W. (2014). Electric vehicles and smart grid interaction: A review on vehicle to grid and renewable energy sources integration. *Renewable & Sustainable Energy Reviews*, *34*(0), 501–516. doi:10.1016/j.rser.2014.03.031

Pan, F., Bent, R., Berscheid, A., & Izraelevitz, D. (2010, October). Locating PHEV exchange stations in V2G. In Smart Grid Communications (SmartGridComm), 2010 First IEEE International Conference on (pp. 173-178). IEEE.

Panigrahi, B. K., Shi, Y., & Lim, M. H. (2011). *Handbook of Swarm Intelligence*. Berlin: Springer. doi:10.1007/978-3-642-17390-5

Preetham, G., & Shireen, W. (2012, January). Photovoltaic charging station for Plug-In Hybrid Electric Vehicles in a smart grid environment. In Innovative Smart Grid Technologies (ISGT), 2012 IEEE PES (pp. 1-8). IEEE. doi:10.1109/ISGT.2012.6175589

Quinn, C., Zimmerle, D., & Bradley, T. H. (2010). The effect of communication architecture on the availability, reliability, and economics of plug-in hybrid electric vehicle-to-grid ancillary services. *Journal of Power Sources*, *195*(5), 1500–1509. doi:10.1016/j.jpowsour.2009.08.075

Sadrnia, A., Nezamabadi-Pour, H., Nikbakht, M., & Ismail, N. (2013). A Gravitational Search Algorithm Approach for Optimizing Closed-Loop Logistics Network. In P. Vasant (Ed.), *Meta-Heuristics Optimization Algorithms in Engineering, Business, Economics, and Finance* (pp. 616–638). Hershey, PA: Information Science Reference. doi:10.4018/978-1-4666-2086-5.ch020

Sandy Thomas, C. (2009). Transportation options in a carbon-constrained world: Hybrids, plug-in hybrids, biofuels, fuel cell electric vehicles, and battery electric vehicles. *International Journal of Hydrogen Energy*, *34*(23), 9279–9296. doi:10.1016/j.ijhydene.2009.09.058

Sarafrazi, S., Nezamabadi-Pour, H., & Saryazdi, S. (2011). Disruption: A new operator in gravitational search algorithm. *Scientia Iranica*, *18*(3), 539–548. doi:10.1016/j.scient.2011.04.003

Singh, J. D. (2012). Nonconvex Economic Load Dispatch Problem with Dynamic Constraint through Gravitational Search Algorithm. *Artificial Intelligent Systems and Machine Learning*, *4*(8), 494–501.

Tate, E. D., Harpster, M. O., & Savagian, P. J. (2008). The electrification of the automobile: from conventional hybrid, to plug-in hybrids, to extended-range electric vehicles (No. 2008-01-0458). SAE Technical Paper.

Tong, S. J., Same, A., Kootstra, M. A., & Park, J. W. (2013). Off-grid photovoltaic vehicle charge using second life lithium batteries: An experimental and numerical investigation. *Applied Energy*, *104*, 740–750. doi:10.1016/j.apenergy.2012.11.046

Tulpule, P., Marano, V., & Rizzoni, G. (2009, June). Effects of different PHEV control strategies on vehicle performance. In *American Control Conference (ACC)*, Montreal, Canada: IEEE. doi:10.1109/ACC.2009.5160595

Vasant, P., Ganesan, T., & Elamvazuthi, I. (2012, January). An improved PSO approach for solving nonconvex optimization problems. In ICT and Knowledge Engineering (ICT & Knowledge Engineering), 2011 9th International Conference on (pp. 80-87). IEEE. doi:10.1109/ICTKE.2012.6152418

Vasant, P. M. (2013). *Handbook of Research on Novel Soft Computing Intelligent Algorithms: Theory and Practical Applications*. IGI Global.

Waraich, R. A., Galus, M. D., Dobler, C., Balmer, M., Andersson, G., & Axhausen, K. W. (2013). Plug-in hybrid electric vehicles and smart grids: Investigations based on a microsimulation. *Transportation Research Part C, Emerging Technologies*, *28*, 74–86. doi:10.1016/j.trc.2012.10.011

Wirasingha, S. G., Schofield, N., & Emadi, A. (2008, September). Plug-in hybrid electric vehicle developments in the US: Trends, barriers, and economic feasibility. In *Vehicle Power and Propulsion Conference*, 2008. IEEE (pp. 1-8). IEEE. doi:10.1109/VPPC.2008.4677702

Wu, J., Wang, J., Li, K., Zhou, H., Lv, Q., Shang, L., & Sun, Y. (2013). Large-Scale Energy Storage System Design and Optimization for Emerging Electric-Drive Vehicles. Computer-Aided Design of Integrated Circuits and Systems. *IEEE Transactions on*, *32*(3), 325–338.

Yang, J., He, L., & Fu, S. (2014). An improved PSO-based charging strategy of electric vehicles in electrical distribution grid. *Applied Energy*, *128*(0), 82–92. doi:10.1016/j.apenergy.2014.04.047

Zeng, J. C., & Cui, Z. H. (2004). A Guaranteed Global Convergence Particle Swarm Optimizer. *Journal of Computer Research and Development, 8,* 1333-1338.

Zhang, L., Brown, T., & Samuelsen, S. (2013). Evaluation of charging infrastructure requirements and operating costs for plug-in electric vehicles. *Journal of Power Sources*, *240*, 515–524. doi:10.1016/j.jpowsour.2013.04.048

Zhou, F. Q., Lian, Z. W., Wang, X. L., Yang, X. H., & Xu, Y. S. (2010). Discussion on operation mode to the electric vehicle charging station. *Power System Protection and Control*, *38*(21), 63–67.

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. Calculating AER is made more complicated because of variations in PHEV design. A vehicle like the Fisker Karma that utilizes a serial hybrid design has a clear AER. Similarly a vehicle like the Chevy Volt which disengages the internal combustion engine (ICE) from the drive train while in electric mode has a clear AER, however blended mode PHEVs which utilize the ICE and electric motor in conjunction do not have a clear AER because they utilize gasoline and grid provided electricity at the same time.

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.

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. Charging itself is simple, once connected to the station charging takes place automatically. The system offers different options for customizing and personalizing charging, including the length of each charge. The control center managing the grid oversees the entire network as well as each individual charge, which enables users to check the operating status of charging stations and any eventual maintenance requirements. The control center also keeps track of each vehicles consumption.

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. The smart grid will make use of technologies, such as state estimation that improve fault detection and allow self-healing of the network without the intervention of technicians. This will ensure more reliable supply of electricity, and reduced vulnerability to natural disasters or attack. Next-generation transmission and distribution infrastructure will be better able to handle possible bi-direction energy flows, allowing for distributed generation such as from photovoltaic panels on building roofs, but also the use of fuel cells, charging to/from the batteries of electric cars, wind turbines, pumped hydroelectric power, and other sources.

State-of-Charge: State-of-Charge (SoC) of a PHEV battery is expressed as the ratio of its capacity of current ($Q(t)$) 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: $SoC = Q(t) / Q_n$. Recently, with the development of artificial intelligence, various new adaptive systems for SOC estimation have been developed .The new developed methods include back propagation (BP) neural network, radial basis function (RBF) neural network, fuzzy logic methods, support vector machine, fuzzy neural network, and Kalman filter. The adaptive systems are self-designing ones that can be automatically adjusted in changing systems. As batteries have been affected by many chemical factors and have nonlinear SOC, adaptive systems offer good solution for SOC estimation.

Vehicle-to-Grid: Vehicle-to-grid (V2G) systems represent a means by which power capacity in parked vehicles can be used to generate electricity for the 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. The benefits of V2G technologies can only be realized if a combination of infrastructure, including regulation, metering and wiring in buildings, electric-drive vehicles, and fuel production and distribution systems are all available.

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.
$\mathbf{I_i(k)}$**:** Charging current over Δt.
$\mathbf{V_i(k)}$**:** Charging voltage over Δt.
$\mathbf{C_{r,i}(k)}$**:** Remaining battery capacity required to be filled for i-th PHEV at time step k.
$\mathbf{C_i}$**:** Rated battery capacity of the i-th PHEV (Farad).
$\mathbf{T_{r,i}(k)}$**:** Remaining time for charging the i-th PHEV at time step k.
$\mathbf{D_i(k)}$**:** Price difference.
$\mathbf{w_i(k)}$**:** Charging weighting term of the i-th PHEV at time step.
$\mathbf{SoC_i(k+1)}$**:** State-of-charge of the i-th PHEV at time step $k+1$.
$\mathbf{SoC_{i,max}}$**:** User-defined maximum battery SoC limit for the i-th PHEV.
J (k): Objective function.
$\mathbf{P_{utility}}$**:** Power available from the utility.
$\mathbf{P_{i,max}}$**:** Maximum power that can be absorbed by a specific PHEV.
η**:** Overall charging efficiency of the charging station.
$\mathbf{\Delta t}$**:** Total charging time.
PSO: Particle swarm optimization.
GSA: Gravitational search algorithm.
M_{aj}**:** Active gravitational mass related to agent j.
M_{pi}**:** Passive gravitational mass related to agent i.
$R_{ij}(t)$**:** Euclidian distance between two agents i and j.
M_{ii}**:** Mass of the object i.
rand_i**:** Random number with interval [0, 1].
*pbest***:** Best value achieved by the individual.
gbest: Best value of the group.
x_i^t**:** Current position of particle i at iteration t.
EMS: Energy management strategy.
EVSE: Electric vehicle supply equipment.
DG: Distributed generation.
DSM: Demand side management.
SMDP: Stochastic semi-Markov decision.