Chapter 9
Plug-in Electric Vehicle Charging Optimization Using Bio-Inspired Computational Intelligence Methods

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9.1 Introduction

Transports which gain most of their energy from the power grid (which includes all-electric vehicles and plug-in hybrid vehicles) have attained noteworthy market diffusion over the past few years [1, 2]. Such transports, commonly mentioned as plug-in electric vehicles (PEVs), lessen the fossil fuel consumption and hence decrease the emissions which includes greenhouse gases [3]. As the number of PEVs are increasing, power system operation will turn out to be more complex [4]. For instance, if a large number of electric vehicles start charging after most people complete their evening commute, a new demand peak could result conceivably demanding ample new power generation capacity as well as ramping capability [5].

The influence of PEVs on the power system has been studied in a few works [6, 7]. Scheduling PEVs charging/discharging profiles is one of the solutions to mitigate the impact of PEVs on the power grid. This can be performed by combining numerous sets of PEVs for charging or discharging with different durations and start times such that grid constraints are properly maintained. Nevertheless, the aggregation of PEVs varies from the aggregation of more conventional power sources [7]. In particular, the temporal availability of PEVs with their precise location information is a significant constraint to study while aggregating PEVs for probable grid congestion management and planning. Therefore, finding suitable charging and discharging times of PEVs that do not disrupt grid constraints while preserving tolerable degrees of customer satisfaction is a challenging optimization problem.

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The earlier generations of electric vehicles are projected to be linked to the power grid only for battery charging. Nevertheless, as the innovative technology develops, the idea of V2G (vehicle-to-grid) will become practically applicable. V2G refers to the technique of injecting power to the grid while being connected to it from vehicle on-board battery. By the help of this system, next-generation PEVs will act as both generators and electric loads, i.e., PEVs will function as energy storage apparatus [8].

During the past few years, several works have been comprehended on bio-inspired optimization techniques. In most of the circumstances, optimum solutions are found by the help of hybrid techniques, particularly on actual-world problems. Earlier, cooperation was mostly comprehended between numerous CI methods. However, currently, gradual cooperation structures between general CI methods with exact tactics are suggested. Hybrid methods typically produce satisfactory results as they are capable of exploiting simultaneous advantages of both kinds of single techniques [9].

It is noteworthy to mention that some of the CI techniques have had their origins in pure science and engineering fields. However, there is a good prospective to explore various hybrid CI methods for solving power system problems as well as their associated theories for future enhancement [4]. Optimization techniques are usually studied as resolving scheduling problems related to PEV, power grid and consumer constraints. Nevertheless, there are other optimization issues like integration of PEV, sizing and placement of charging stations.

The remaining segments are organized as per the following way: Sect. 9.2 discusses the charging of plug-in electric vehicle (PEV), Sect. 9.3 highlights the PEV charging optimization issues, Sect. 9.4 describes the bio-inspired computational intelligence (CI) techniques, Sect. 9.5 discusses the applications of bio-inspired CI for PEV charging optimization, and finally, Sect. 9.6 concludes the chapter with future research directions.

9.2 Charging of Plug-in Electric Vehicle (PEV)

The PEV charging can be categorized into three different ways depending on the charging voltage level and locations. Figure 9.1 provides the schematic diagrams of different PEV charging alternatives.

The classifications of PEV based on the charging level are briefed below.

9.2.1 Level 1 Charging

Household-type socket-outlet is used for AC Level 1 slow charging. The best public choice for PEV charging is Level 1 type because of the usage of conventional

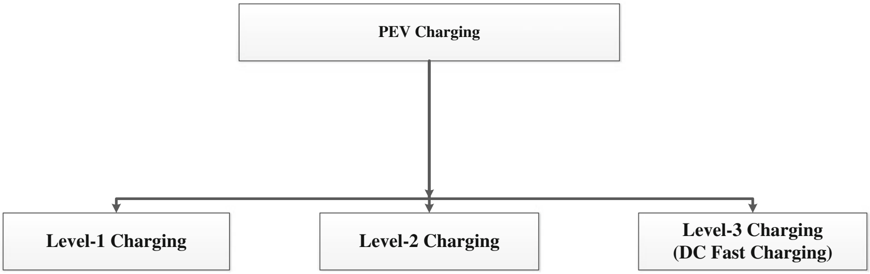

Fig. 9.1 Different types of PEV charging [10]

industrial/house socket. Level 1 type of charging is presently regarded as the key mode for small-sized PEVs like two wheelers [10].

9.2.2 Level 2 Charging

Slow charging from a household-type socket with an in-cable protection device is used for AC Level 2 charging which also permits the usage of conventional industrial/house socket [10]. Nonetheless, this type of charging delivers extra shield by adding an in-cable control box with a control pilot conductor amid the PEVs and control box or the plug.

9.2.3 Level 3 Charging (DC Fast Charging)

DC fast charging is used as an external charger. There are 2 sub-mode types of operation measured for the mode, specifically, the DC Level 1 (current <80 A, voltage <500 V, power = 40 kW) and the DC Level 2 (current <200 A, voltage <500 V, power = 100 kW) [10].

It is noteworthy to indicate that in Level 1 type, there is no physical communication between the charging point through the connector and PEVs. In Level 2 type, a pilot communication system can be added by permitting charging rate control. Meanwhile, Level 3 type is mostly utilized for fast charging purposes which is DC. A communication system is involved in Level 3 type of charging which allows the management of appropriate battery charging. Furthermore, in Level 2 and Level 3 types of charging, wireless communication networks can be utilized to interconnect with PEVs as well as to control the charging and discharging progression.

9.3 PEV Charging Optimization Issues

Scientists are now putting efforts to minimize certain parameters like life-cycle costs for the operation and installation of charging infrastructure, extra loads on charging station as well as to maximize the overall revenues, integration of renewable energy sources (RESs) and average state of charge (SoC) [11]. Furthermore, expert systems based on real-time simulation, enhanced charging schemes and optimal power allocation for PEVs have drawn ample consideration among the researchers.

Kulshrestha et al. in [12] proposed concurrent smart energy management of PHEVs for optimum usage of available power, charging duration and grid stability. Furthermore, consumer approval, loads conditions, SoC and storage capability are included. The benefits of using electric vehicles as energy storage for demand-side management are addressed by Pang et al. [13]. Herrera et al. developed hardware-in-loop simulation platform [14] for continuous (power systems and power electronics) as well as discrete (communication systems) constraints. Sizing optimization of the local energy storage (LES) for PEV charging was created within an overall cost-minimization agenda by the authors in [15]. The control mechanism of PHEV charging stations with LES facility was established. The results showed the superiority of proposed systems with optimized parameters during both the islanding and grid-connected modes as well as the transitional period with minimized voltage. Lu et al. [16] studied large-scale behavior of vehicle charging, deployment of charging infrastructure and driving pattern for PHEVs. Extensive analysis was performed considering PHEV charging and driving dataset and responded specific research questions on PHEV's interaction to traditional power grid network. Lastly, the researchers recommended the need of real-time driving data with global optimization techniques.

Tulpule et al. [17] formulated improved equivalent consumption minimization strategy (ECMS) for electric vehicle control by considering total energy consumption factor together with the constant SoC maintenance of vehicle battery. As a result, the SoC is dictated by ECMS at a persistent position with low consumption of fuel. Tehrani et al. [18] characterized the fast charging infrastructures' operation equipped with energy storage and RESs in order to optimize the charging pattern and retailing power to the existing grid by following the price variations to maximize the fitness function for the benefit of contributing to the electricity market. In [19], the fitness function was to reduce the total cost. In [20], the fitness function was to maximize the utilization of renewable energy and to minimize the charging cost. The optimization constraints are the size and charging rate of the battery. In [21], the objective was to guarantee fast charging duration of battery without the overheating. Moreover, in [22], the objective was profit maximization of PEVs. The authors provided different optimization objectives and certain system constraints with the simulated data. Conferring to the type of the optimization problems addressed, the authors suggested the estimation of distribution algorithm (EDA) to appropriately control numerous batteries charging/discharging from a bunch of electric vehicles.

The capability of PEVs to facilitate the renewable energy integration to the existing power system networks is possibly the most significant influence on power grid [23]. Placement of all-encompassing photovoltaic (PV) charging arrangement in an EV parking area was described by Neumann et al. [24]. Charging in PV parking lot and diverse business models considering solar energy were discussed by Rizzo et al. [25]. Environmental and socioeconomic influences of PV-based office charging infrastructure were addressed in [26]. The study specified the technical feasibility of establishing a PV-integrated office parking facility considering profits for the car owner as compared to the household facilities of charging. Authors stated that the consumer will receive the return of establishment and maintenance cost as well as profit within the lifespan of the PV panels. Birnie [27] introduced a solar collector integrated parking shade by encouraging the widespread installation of solar system module and concluded that the system will allow much more rapid payback period. In [28], Zhang et al. explained optimal control approaches to integrate both the PEVs and PV considering the existing power grid.

9.4 Bio-Inspired Computational Intelligence (CI)

Nature is certainly an enormous and potential source of motivation for solving complex problems in the domain of computer science as it shows very dynamic, diverse, complex and robust phenomenon [29]. It regularly finds the optimal solution to solve its problem keeping balance between exploration and exploitation. This is the thrust behind bio-inspired computational intelligence (CI). Bio-inspired CI techniques have the advantages as follows:

i. The stochastic and population-based nature of bio-inspired CI can significantly increase its search space and hence lessen the chance of trapping into local optima compared to the classical local optimization methods such as hill-climbing and gradient-based techniques which are employed on deterministic rules.
ii. Bio-inspired CI is focused toward better regions of a search space compared to the ineffective random search technique because it accurately uses fitness functions rather than function derivatives.

Bio-inspired CI techniques are very diverse and can be put into 3 categories: evolution based, swarm based and ecology based. It is important to mention that such categorization is not rigorous. Nonetheless, it is primarily done for the ease of discussions in the chapter. A brief taxonomy of bio-inspired CI techniques is shown in Fig. 9.2.

Črepinšek et al. [30] offered some basic guidelines to conduct any replications and comparisons of evolutionary computation-based algorithms for optimization.

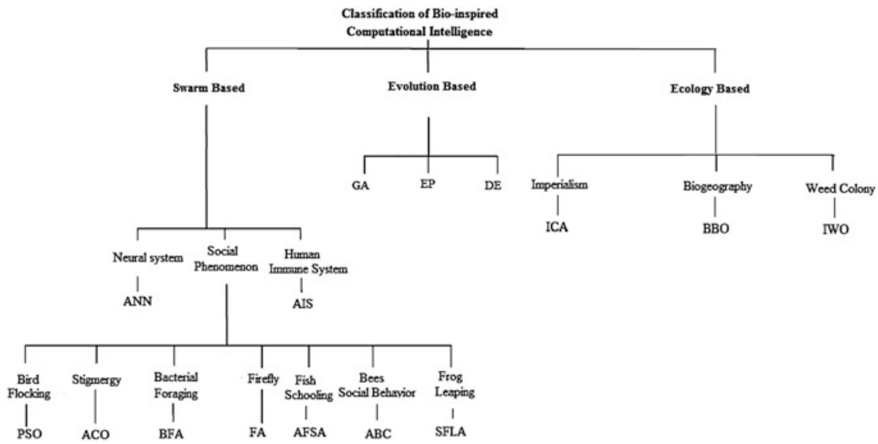

Fig. 9.2 Taxonomy of bio-inspired CI techniques

Moreover, the comparisons conducted should be based on suitable performance measures and able to show statistical significance of one approach over others. If the simulation study is not carried out with adequate caution, any statistical methods and performance measures cannot get rid of the problems adapted by inaccurate simulation replication. Defining suitable performance measures are the basis for algorithm comparisons. Hence, performance measures must be carefully defined and described. Exact replication cannot always be attained. All deviations must be stated. Any changes to the original experiment should be openly discussed along with a description of the inspiration for the changes, as well as any threats to the validities of the conclusions [31].

9.5 Applications of Bio-Inspired CI for PEV Charging Optimization

In this section, the bio-inspired CI techniques often used in the charging optimization are presented.

9.5.1 Charge Scheduling Optimization

By the appropriate establishment of intelligent scheduling techniques, smooth integration of PEVs onto the power grid can be attained. Smart scheduling techniques will assist to avoid cycling of bulky combustion plants, using costly fossil fuel peaking plant by introducing PEVs in power system networks.

Bio-inspired CI techniques are alternative optimization tools to deal with the non-smooth and complex power grid scheduling particularly with the latest deployment of electric vehicles with dubiety and well-regulated charging loads [32]. Moreover, the bio-inspired CI techniques uphold stochastic types of solutions as well as guide them toward optimal solutions through heuristic approaches. These methods are typically not certain toward global optimum achievement, but are generally resistant to high-dimensional, non-convex and nonlinear systems because of this process. Therefore, the mentioned techniques are widespread selections for elucidating the constraints and fitness functions which are not endlessly differentiable like binary charging/discharging scenarios considering an enormous PEV.

Authors used ant colony optimization (ACO) for transformer side charging scheduling of PEVs [33]. They concluded that the computation burden of ACO is relatively low and thus suitable for large-scale application. The simulation results relate and compare the load charging curve of PEV with the effect of load fluctuation. The authors also proposed an intelligent charging algorithm for electric vehicle charging services in reaction to TOU price. The aim was to improve the stress in power grid under peak demand and to meet the demand response requirements in regulated market. Authors in another work introduced a centralized scheduling policy for PEV charging using genetic algorithm (GA) to facilitate the size and complexity of the optimization [34]. The load curve shape remained relatively consistent. Thus, the algorithm attained statistically similar results from run to run. This validated the formulated optimization approach and algorithm for PEV charge scheduling.

In Soares et al., 3 variants of PSO techniques were formulated for comparison [35]. The authors concluded that, with the rise of decision variables, the overall computational complexity prolonged exponentially. From the results analysis, authors concluded that EPSO obtained better solution quality with reasonable execution time for the problem context (day ahead). Moreover, ant colony optimization (ACO) was utilized to improve the binary PSO for the optimization of unit commitment (UC)-related problem due the PEV load suggested by the authors in [36]. The scheduling was handled by binary PSO based on logical operators, and economic dispatch was solved through an improved ACO. The best cost per produced unit (CPU) procedure was implemented in the suggested technique to decrease the maximum required iteration in BPSO.

Roy and Govardhan examined the economic cost of UC with the generation of wind energy, emergency demand response, PEV charging and discharging using teaching-learning-based optimization (TLBO) algorithm [37]. The study indicated that the operational cost reduction is possible by the expansion of PEV battery capacity. Nonetheless, additional cost on transmission congesting and battery depletion exists among the challenges of PEV operation in power grid networks.

Proper charging scheduling is needed for upcoming PEV penetration in the vehicular network. There exists 'range anxiety' among the owners of PEVs. They are worried about the electric vehicle mileage because the on-board storage needs to be charged when the state of charge reaches a certain limit [38]. Uncoordinated fashioned PEV charging is the source of disturbances to the power grid, i.e., lines and transformers overload and voltage drops [39].

Hybrid optimization techniques perform a noticeable role in enhancing any search techniques. Hybrid techniques are used to combine the benefits of two or more algorithms, while concurrently trying to curtail any considerable drawbacks [40]. Overall, the effect of hybrid techniques can typically make some developments considering solution accuracy and computational complexity [41].

9.5.2 Optimal Charging Strategy

One of the most recent charging strategies of PEVs is smart charging [42]. The awareness behind this smart charging is based on PEV charging during the most advantageous scenarios when the electricity demand and price is the lowest with surplus capacity [43].

Authors in [44] used artificial immune system (AIS) and tangent vector (TV) technique for PEV recharging policy of IEEE 34-bus distribution system. The results of the TV-based optimization method demonstrated loss reduction with a lesser computational complexity by the help of random search process. Nevertheless, the authors suggested simulation for larger distribution systems as a future research.

Authors in [38] did a trade-off between power management strategy of stochastic optimal PEV and electrochemistry-based model of anode-side resistive film formation in lithium-ion batteries using a non-dominated sorting genetic algorithm (NSGA) in the formation of a Pareto front. Authors applied NSGA-II to the plug-in EV model in order to find its optimum charging patterns. After comparing various solutions from the Pareto front, the authors suggested that consumer should preferably charge a plug-in EV rapidly during off-peak hours and just before the onset of traveling to efficiently reduce energy costs and battery degradation.

Different PSO variants were utilized to optimize other PEV charging-related parameters. In [39], the fitness function was to maximize the average SoC in terms of the battery capacity, energy cost and remaining PEV charging time which is very nonlinear in nature and tough to resolve by traditional optimization techniques. The authors proposed adaptive weight PSO-based algorithm and compared with interior point method (IPM) and GA techniques. The suggested technique outperforms both IPM and GA considering exploitation capability. This demonstrates the superiority of bio-inspired algorithm.

Poursistani et al. [45] used an optimization technique founded on binary type of gravitational search algorithm (BGSA) in order to plan the optimal charging of PEVs. The results showed positive effect of smart charging using BGSA technique for the peak shaving of load.

Rahman et al. employed accelerated particle swarm optimization (APSO) [46] and hybrid particle swarm optimization and GSA (PSO-GSA) [47] for SoC maximization of PEVs, hence optimizing the overall smart charging. The hybrid

Table 9.1 A summary of different bio-inspired CI techniques for PEV charging optimization

Authors and references	Applications	Bio-inspired CI technique	Year
Xu et al. [33]	Charge scheduling optimization	ACO	2013
Crow [34]		GA	2014
Soares et al. [35]		PSO	2013
Ghanbarzadeh et al. [36]		ACO, HPSO	2011
Govardhan and Roy [37]		TLBO	2015
Rorigues et al. [44]	Optimal charging strategy	AIS	2013
Bashash et al. [38]		NSGA	2011
Su and Chow [39]		PSO	2012
Poursistani et al. [45]		BGSA	2015
Rahman et al. [46]		APSO	2016
Vasant et al. [47]		PSO-GSA	2016
Awasthi et al. [49]		GA-PSO	2017

PSO-GSA uses the benefits of both GSA and PSO techniques and thus obtains optimum fitness values. Nevertheless, PSO-GSA technique shows much higher computational time compared to single techniques because of complex algorithm formulation. Normally, hybrid bio-inspired methods produce good results for best fitness value. However, the computational time is longer compared to single method [48] because more parameters initialization is needed due to two different methods working in parallel in the hybrid algorithm.

Moreover, Awasthi et al. hybridized GA with an enhanced variant of the particle swarm optimization (GAIPSO) in order to find best location for suggested charging strategy in the Allahabad power distribution company, India [49]. Simulation analysis on a real-time Allahabad city power system clearly shows the superior capability of the stated method compared to PSO and GA to optimize the fitness function considering voltage profile improvement and solution quality.

Table 9.1 summarizes a number of very recent bio-inspired CI techniques applied for the discussed applications of PEV charging optimization.

9.6 Summary and Conclusion

Scientists from multi-disciplinary research backgrounds should try to apply the theoretical knowledge to solve real-time PEV charging problems. Researchers from various backgrounds such as architecture, civil engineering, mechanical engineering and electrical engineering should put painstaking effort together in order to realize successful PEV charging optimization in smart grid. The application of bio-inspired CI techniques for PEV charging optimization is an emerging research field eliciting considerable research attention. The discussions in Sect. 9.5 demonstrate that the overall performances of various bio-inspired CI techniques (specially, PSO, GA) in this domain are very noteworthy as they will inspire other researchers to formulate latest bio-inspired CI techniques to optimize PEV charging. Judging from the trend, interesting variants in this area are hybrid bio-inspired CI such as GA-PSO [47] and PSO-GSA [49] as the results have been found to be highly competitive compared to single CI techniques.

In the future, it is suggested that some well-performed bio-inspired CI techniques like cuckoo search algorithm (CSA), artificial bee colony (ABC) and artificial fish swarm algorithm (AFSA) should be applied to solve issues related to PEV charging. As CSA [50] is constructed on the brood parasitism behavior of cuckoo species and because it uses levy flights, the method can be used for solving PEV complex problems. Levy flight is able to give better result than simple random walk. Moreover, artificial bee colony (ABC) technique is lately presented swarm-based optimization methods which mimics the clever honeybee swarm foraging behavior [51]. It is encouraged that future studies for solving smart charging problem of PEV involve the ABC optimization technique. Furthermore, integrating new or modified hunting behavioral strategies adapted from other bio-inspired algorithms into the swarming behavior stage of AFSA should be able to enhance its convergence rates and optimal solutions of PEV charging [52]. Although various bio-inspired CI techniques have been presented to perform better optimization than that of the standalone versions, the 'No Free Lunch (NFL)' theory [53] is a fundamental barrier toward the overstated claims of the efficiency and robustness of any particular optimization techniques. Particularly, in practice, there is no single optimization technique that can perform best for all types of power system optimization problems. Hence, one potential approach to handle the undesirable implication of the NFL theory is to formulate algorithms based on the synthesis of existing ones as well as limit the applications of a given algorithm to only a specific type of PEV charging optimization problems.

References

1. I. Rahman, P.M. Vasant, B.S.M. Singh, M. Abdullah-Al-Wadud, Intelligent energy allocation strategy for PHEV charging station using gravitational search algorithm, in *AIP Conference Proceedings* (2014), pp. 52–59
2. N. Adnan, S.M. Nordin, I. Rahman, Adoption of PHEV/EV in Malaysia: a critical review on predicting consumer behaviour. Renew. Sustain. Energy Rev. **72**, 849–862 (2017)
3. N. Adnan, S.M. Nordin, I. Rahman, P.M. Vasant, A. Noor, A comprehensive review on theoretical framework-based electric vehicle consumer adoption research. Int. J. Energy Res. (2016)
4. Q. Wang, X. Liu, J. Du, F. Kong, Smart charging for electric vehicles: a survey from the algorithmic perspective. IEEE Commun. Surv Tutorials **18**, 1500–1517 (2016)
5. M.H. Amini, M.P. Moghaddam, O. Karabasoglu, Simultaneous allocation of electric vehicles' parking lots and distributed renewable resources in smart power distribution networks. Sustain. Cities Soc. **28**, 332–342 (2017)

6. H. Shareef, M.M. Islam, A. Mohamed, A review of the stage-of-the-art charging technologies, placement methodologies, and impacts of electric vehicles. Renew. Sustain. Energy Rev. **64**, 403–420 (2016)
7. J. Hu, H. Morais, T. Sousa, M. Lind, Electric vehicle fleet management in smart grids: a review of services, optimization and control aspects. Renew. Sustain. Energy Rev. **56**, 1207–1226 (2016)
8. Z. Yang, K. Li, A. Foley, Computational scheduling methods for integrating plug-in electric vehicles with power systems: a review. Renew. Sustain. Energy Rev. **51**, 396–416 (2015)
9. E.S. Rigas, S.D. Ramchurn, N. Bassiliades, Managing electric vehicles in the smart grid using artificial intelligence: a survey. IEEE Trans. Intell. Trans. Syst. **16**, 1619–1635 (2015)
10. A. Foley, I. Winning, B.Ó. Gallachóir, State-of-the-art in electric vehicle charging infrastructure, in *2010 Vehicle Power and Propulsion Conference (VPPC)* (IEEE, 2010), pp. 1–6
11. F. Mwasilu, J.J. Justo, E.-K. Kim, T.D. Do, J.-W. Jung, Electric vehicles and smart grid interaction: a review on vehicle to grid and renewable energy sources integration. Renew. Sustain. Energy Rev. **34**(6), 501–516 (2014)
12. P. Kulshrestha, L. Wang, M.-Y. Chow, S. Lukic, Intelligent energy management system simulator for PHEVs at municipal parking deck in a smart grid environment, in *2009 Power and Energy Society General Meeting, PES'09.* (IEEE, 2009), pp. 1–6
13. C. Pang, P. Dutta, S. Kim, M. Kezunovic, I. Damnjanovic, PHEVs as dynamically configurable dispersed energy storage for V2B uses in the smart grid, in *IET Conference Proceedings* (2010), pp. 174–174, http://digital-library.theiet.org/content/conferences/10.1049/cp.2010.0903
14. L. Herrera, R. Murawski, F. Guo, E. Inoa, E. Ekici, and J. Wang, PHEVs charging stations, communications, and control simulation in real time, in *Vehicle Power and Propulsion Conference (VPPC)* (IEEE, 2011), pp. 1–5
15. E. Inoa, F. Guo, J. Wang, W. Choi, A full study of a PHEV charging facility based on global optimization and real-time simulation, in *2011 IEEE 8th International Conference on Power Electronics and ECCE Asia (ICPE & ECCE)* (2011), pp. 565–570
16. Z. Ren, H. Jiang, J. Xuan, Z. Luo, Hyper-heuristics with low level parameter adaptation. Evol. Comput. **20**, 189–227 (2012)
17. P. Tulpule, V. Marano, G. Rizzoni, Effects of different PHEV control strategies on vehicle performance, in *2009 American Control Conference, ACC'09* (2009), pp. 3950–3955
18. N.H. Tehrani, G. Shrestha, P. Wang, Optimized power trading of a PEV charging station with energy storage system, in *IPEC* (2012), p. 305
19. F. Pan, R. Bent, A. Berscheid, D. Izraelevitz, Locating PHEV exchange stations in V2G, in *2010 First IEEE International Conference on Smart Grid Communications (SmartGridComm)* (2010), pp. 173–178
20. A. Elgammal, A. Sharaf, Self-regulating particle swarm optimised controller for (photovoltaic-fuel cell) battery charging of hybrid electric vehicles. Electr. Syst. Trans. IET **2**, 77–89 (2012)
21. F. Fazelpour, M. Vafaeipour, O. Rahbari, M.A. Rosen, Intelligent optimization to integrate a plug-in hybrid electric vehicle smart parking lot with renewable energy resources and enhance grid characteristics. Energy Convers. Manag. **77**, 250–261 (2014)
22. W. Su, *Performance Evaluation of an EDA-Based Large-Scale Plug-In Hybrid Electric Vehicle Charging Algorithm* (2012)
23. M.H. Amini, A. Kargarian, O. Karabasoglu, ARIMA-based decoupled time series forecasting of electric vehicle charging demand for stochastic power system operation. Electr. Power Syst. Res. **140**, 378–390 (2016)
24. H.M. Neumann, D. Schär, F. Baumgartner, The potential of photovoltaic carports to cover the energy demand of road passenger transport. Prog. Photovoltaics Res. Appl. **20**, 639–649 (2012)
25. G. Rizzo, I. Arsie, M. Sorrentino, Solar energy for cars: perspectives, opportunities and problems, in *GTAA Meeting* (2010), pp. 1–6

26. P.J. Tulpule, V. Marano, S. Yurkovich, G. Rizzoni, Economic and environmental impacts of a PV powered workplace parking garage charging station. Appl. Energy **108**, 323–332 (2013)
27. D.P. Birnie, Solar-to-vehicle (S2V) systems for powering commuters of the future. J. Power Sources **186**, 539–542 (2009)
28. Q. Zhang, T. Tezuka, K.N. Ishihara, B.C. Mclellan, Integration of PV power into future low-carbon smart electricity systems with EV and HP in Kansai Area, Japan. Renew. Energy **44**, 99–108 (2012)
29. S. Binitha, S.S. Sathya, A survey of bio inspired optimization algorithms. Int. J. Soft Comput. Eng. **2**, 137–151 (2012)
30. M. Črepinšek, S.-H. Liu, M. Mernik, Exploration and exploitation in evolutionary algorithms: a survey. ACM Comput. Surv. (CSUR) **45**, 35 (2013)
31. M. Črepinšek, S.-H. Liu, M. Mernik, Replication and comparison of computational experiments in applied evolutionary computing: common pitfalls and guidelines to avoid them. Appl. Soft Comput. **19**, 161–170 (2014)
32. X.-S. Yang, Z. Cui, R. Xiao, A.H. Gandomi, M. Karamanoglu, *Swarm Intelligence and Bio-Inspired Computation: Theory and Applications* (Newnes, 2013)
33. S. Xu, D. Feng, Z. Yan, L. Zhang, N. Li, L. Jing, et al., Ant-based swarm algorithm for charging coordination of electric vehicles. Int. J. Distrib. Sens. Netw. (2013)
34. M.L. Crow, Economic scheduling of residential plug-in (hybrid) electric vehicle (PHEV) charging. Energies **7**, 1876–1898 (2014)
35. J. Soares, H. Morais, Z. Vale, Particle swarm optimization based approaches to vehicle-to-grid scheduling, in *2012 Power and Energy Society General Meeting* (IEEE, 2012), pp. 1–8
36. T. Ghanbarzadeh, S. Goleijani, M.P. Moghaddam, Reliability constrained unit commitment with electric vehicle to grid using hybrid particle swarm optimization and ant colony optimization, in *2011 Power and Energy Society General Meeting* (IEEE, 2011), pp. 1–7
37. M. Govardhan, R. Roy, Economic analysis of unit commitment with distributed energy resources. Int. J. Electr. Power Energy Syst. **71**, 1–14 (2015)
38. S. Bashash, S.J. Moura, J.C. Forman, H.K. Fathy, Plug-in hybrid electric vehicle charge pattern optimization for energy cost and battery longevity. J. Power Sources **196**, 541–549 (2011)
39. W. Su, M.-Y. Chow, Performance evaluation of a PHEV parking station using particle swarm optimization, in *2011 Power and Energy Society General Meeting* (IEEE, 2011), pp. 1–6
40. I. Fister, D. Strnad, X.-S. Yang, I. Fister Jr, Adaptation and hybridization in nature-inspired algorithms, in *Adaptation and Hybridization in Computational Intelligence* (Springer, 2015), pp. 3–50
41. B. Xing, W.-J. Gao, *Innovative Computational Intelligence: A Rough Guide to 134 Clever Algorithms*, vol. 62 (Springer, 2014)
42. P.-Y. Kong, G.K. Karagiannidis, Charging schemes for plug-in hybrid electric vehicles in smart grid: a survey. IEEE Access **4**, 6846–6875 (2016)
43. I. Rahman, P.M. Vasant, B.S.M. Singh, M. Abdullah-Al-Wadud, Novel metaheuristic optimization strategies for plug-in hybrid electric vehicles: a holistic review. Intell. Decision Technol. **10**, 149–163 (2016)
44. Y.R. Rorigues, M.F. Souza, B. Lopes, A. Souza, D. Oliveira, Recharging process of plug in vehicles by using artificial immune system and tangent vector (2013)
45. M. Poursistani, M. Abedi, N. Hajilu, G. Gharehpetian, Smart charging of plug-in electric vehicle using gravitational search algorithm, in *2014 Smart Grid Conference (SGC)* (2014), pp. 1–7
46. I. Rahman, P.M. Vasant, B.S.M. Singh, M. Abdullah-Al-Wadud, On the performance of accelerated particle swarm optimization for charging plug-in hybrid electric vehicles. Alexandria Eng. J. **55**, 419–426 (2016)
47. P.M. Vasant, I. Rahman, B. Singh Mahinder Singh, M. Abdullah-Al-Wadud, Optimal power allocation scheme for plug-in hybrid electric vehicles using swarm intelligence techniques. Cogent Eng. **3**, 1203083 (2016)

48. T. Ting, X.-S. Yang, S. Cheng, K. Huang, Hybrid metaheuristic algorithms: past, present, and future, in *Recent Advances in Swarm Intelligence and Evolutionary Computation* (Springer, 2015), pp. 71–83
49. A. Awasthi, D. Chandra, S. Rajasekar, A.K. Singh, K.M. Perumal, Optimal infrastructure planning of electric vehicle charging stations using hybrid optimization algorithm, in *2016 Power Systems Conference (NPSC)* (National, 2016), pp. 1–6
50. M. Basu, A. Chowdhury, Cuckoo search algorithm for economic dispatch. Energy **60**, 99–108 (2013)
51. N. Sulaiman, J. Mohamad-Saleh, A.G. Abro, A modified artificial bee colony (JA-ABC) optimization algorithm, in *Proceedings of the International Conference on Applied Mathematics and Computational Methods in Engineering* (2013), pp. 74–79
52. M. Neshat, G. Sepidnam, M. Sargolzaei, A.N. Toosi, Artificial fish swarm algorithm: a survey of the state-of-the-art, hybridization, combinatorial and indicative applications. Artif. Intell. Rev. 1–33 (2014)
53. D.H. Wolpert, W.G. Macready, No free lunch theorems for optimization. IEEE Trans. Evol. Comput. **1**, 67–82 (1997)