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Novel metaheuristic optimization strategies for plug-in hybrid electric vehicles: A holistic review

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Abstract. Hybrid Vehicles have experienced major modifications since the last decade. Smart grid success with combination of renewable energy exclusively depends upon the large-scale penetration of Plug-in Hybrid Electric Vehicles (PHEVs) for a sustainable and carbon-free transportation. Recent technical studies regarding various optimization strategies related to PHEV integrated smart grid; such as control and battery charging, vehicle-to-grid (V2G), unit commitment, charging infrastructures, integration of solar and wind energy and demand management prove that electrification of transportation as a rapidly growing field of research. This work presents a holistic review of all substantial research applying metaheuritics optimization for plug-in-hybrid electric vehicles. A summary on future perspective of metaheuristic algorithms is also provided, covering Cuckoo Search (CS), Harmony Search (HS), Artificial Bee Colony (ABC), etc. with a comprehensive reviews on previously applied methods and their performance for solving different real-world problems in the domain of PHEVs. Moreover, significant shifts towards hybrid and hyper metaheuristics are also highlighted.

Keywords: PHEV, metaheuristic, optimization, swarm intelligence, literature review, smart grid

Nomenclature

ABC	Artificial Bee Colony
ACO	Ant Colony Optimization
AER	All Electric Range
AEV	All Electric Vehicle
AIS	Artificial Immune System
BEV	Battery Electric Vehicle
CS	Cuckoo Search
DDFA	Dynamic Discrete Firefly Algorithm
DE	Differential Evolution
DPSO	Dynamic Particle Swarm Optimization
EC	Evolutionary Computation
EP	Evolutionary Programming
FCEV	Fuel Cell Electric Vehicle
GA	Genetic Algorithm
GABFO	Genetic-based bacteria foraging algorithm
GP	Genetic Programming
GSA	Gravitational Search Algorithm
HEV	Hybrid Electric Vehicle
HIGA	Hybrid Improved Genetic Algorithm
HS	Harmony Search
ICEV	Internal Combustion Engine Vehicles
LA	Liner Approximation
LP	Linear Programming
MOGA	Multi-objective Genetic Algorithm
NSGA	Non-dominated Sorting Genetic Algorithm
PHEVs	Plug-in Hybrid Electric Vehicle
PM	Particulate Matter
PSAGADO	Particle Swarm And Genetic Algorithm with Downhill-simplex Optimization
PSO	Particle Swarm Optimization

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PSOGSA	Hybrid Particle Swarm Optimization and Gravitational Search Algorithm
QA	Quadratic Approximation
QP	Quadratic Programming
RESs	Renewable Energy Sources
SAAHGA	Simulated Annealing, Adaptive based Hybrid Genetic Algorithm
SFA	Stationary Firefly Algorithm
SI	Swarm Intelligence
SoC	State-of-Charge
SPWM	Sinusoidal Pulse Width Modulation
SQP	Sequential Quadratic Programming
SVPW	Space-Vector Pulse Width Modulation
TV	Tangent Vector
V2G	Vehicle-o-Grid

1. Introduction

Global climate variation has been getting growing attention lately. However, minimizing emissions of air contaminants [such as nitrogen oxides (NOx), sulphur dioxide (SO2) and Particulate Matter (PM)] is a more crucial problem, predominantly for developing regions. Among all the pollution producing sectors, the road transport sector is one of the major cause for air pollution [1]. Carbon dioxide is the main greenhouse gas emitted through human activities like combustion of fossil fuels (coal, natural gas, and oil) for energy and transportation. Numerous researchers have come into a conclusion that modern day transport sector will gradually be more electrified and expected to play a progressively larger role toward shifting a portion of the transportation energy burden towards other sources and away from tradition fuel like petroleum [2]. Certainly, the acceptance of hybrid electric vehicles (HEVs) has brought significant market success over the past decade. Vehicles can be classified into three groups: internal combustion engine vehicles (ICEV), hybrid electric vehicles (HEV) and all-electric vehicles (AEV) [3]. Recently introduced Plug-in hybrid electric vehicles (PHEVs) has the potential to rise the total fuel efficiency because of a large size on board battery charged directly from the traditional electric grid, that supports the automobiles to function uninterruptedly in "All-Electric-Range" (AER). All-electric vehicles or AEV is a vehicle using electric power as only sources to move the vehicle [4]. PHEVs with a linkage to the new generation grid namely smart grid system can own state-of-art strategies. In near future, electric-powered vehicles will be plugged into the grid, and their on board energy storage systems will be recharged using clean, renewable electricity. Hence, the broader implementation of PHEVs might perform a substantial role in the unconventional energy integration into traditional grid systems [5]. As a result, well-organized optimization strategies for electric vehicle technologies are needed in order to solve extremely diverse problems like energy management, cost reduction, efficient charging infrastructure etc. with different objectives and system constraints.

Metaheuristics are broadly recognized as effective tactics for numerous hard optimization glitches which is very tough to solve within given constraints, exact fixed method and within a desired time duration [6]. Certainly, the word "meta" stems from the Greek prefix entitles that these techniques are high level heuristics, in distinction with problem-oriented heuristics. When there is no satisfactory problem-specific algorithm to solve any particular optimization problem, then metaheuristics are mostly applied to problems. Metaheuristics are extensively used to solve complex real-world problems in industries and engineering farms, in fields extending from economics to supply chain management. In the domain of PHEVs, very few survey papers [7,8] deal with the optimization perspectives along with their applications and among those, no paper highlights the metaheuristic optimization strategies for PHEVs as far the past literatures have concerned. The motivation of this paper comes from this vacuum of PHEV optimization-related survey literatures. In this paper, various research on optimization problems are identified and the equivalent literature is extensively surveyed in order to address different optimization challenges and solution measures.

The aim of this review paper is to provide a comprehensive overview of different metaheuristics techniques along with their pros and cons for solving different PHEVs optimization problems. The overall review on metaheuristics is organized in the following approach. Section 2 briefly presents the definition of PHEVs as well as various types of electric vehicles. Section 3 defines metaheuristic optimization strategies and their characteristics. Section 4 focuses on the classifications of different metaheuristic techniques including evolutionary algorithms, swarm intelligence algorithms, fuzzy logic etc. PHEV optimization problems and solution approaches are described in Section 5 along with the controlling principles of selecting and applying metaheuristic optimization algorithms for particular problem. Section 6 shows the advantages and disadvantages of the metaheuristics approaches as per the previous research findings through the computational results. Future research directions in Section 7 includes the description of hybrid evolutionary swarm optimization and hyper-heuristics optimization techniques. Finally, the review concludes with some discussions and conclusion in Sections 8 and 9 respectively.

2. Plug-in hybrid electric vehicles

There are many alternatives that have been suggested by the researchers in order to reduce the dependence on traditional fuel by introducing the concepts like sustainable fuel sources, alternative transport solution etc. Among the alternative solutions of traditional vehicle, electric propulsion system-based vehicles have introduced considering the environment friendly option in mind. Hybrid electric vehicles (HEVs) are now available on roads with the addition of traction motor which is electric as well as on board storage system like batteries. The on-board storage system is different system architecture compared to traditional ICEV [7]. The upgraded and more pollution-free alternative of HEV is the plug-in hybrid electric vehicle (PHEV) that has on board storage system with the facilities of charging form power grid and renewable energy sources while parked. As a result, electricity replaces the fuel like gasoline, patrol. The final target in the revolution of electrification is to exclude the old fashioned internal combustion engine hence start the new era of in AEV (All-Electric-Vehicle). Fuel cell electric vehicle (FCEV) and battery electric vehicle (BEV) are the two most recent all-electric type vehicles under attention. FCEV is driven by hydrogen whereas BEV solely depend for all its energy on the electrical power grid.

3. Metaheuristic optimization strategies

"A metaheuristic is conventionally described as an iterative generation process which guides a servant heuristic by combining intelligently different concepts for exploring and exploiting the search space, learning strategies are used to structure information in order to find efficiently near-optimal solutions" [9]. Certainly, the Greek prefix "Meta" is used to indicate that these algorithms are "higher level" heuristic, in contrast with problem-specific heuristics. Metaheuristic methods are using for solving different complex optimization problems. In any metaheuristic algorithm there are some initial solutions from which candidate solutions are created. After that, each solution is evaluated and the algorithm choose the best solution. If the stopping criteria is met, then the algorithm will produce final solution otherwise it will again search for best solutions from the initial step. Proper balance between exploration and the exploitation is the basic criteria to analyze the performance of a metaheuristic. Proper exploration will diversify the search space of an optimization technique whereas the exploitation ensures the high quality solutions. Researchers are trying to make appropriate balance between these two criteria of any optimization problem. Desired values for the fitness function can only be possible if there is accurate balancing [10]. Without proper balance any particular Method cannot achieve their goal to optimize any fitness function.

4. Classifications of metaheuristic optimization

Metaheuristic optimization methods are classified mainly into eight categories such as: Evolutionary Algorithms, Stochastic Algorithms, Swarm Intelligence Algorithms, Physics-related Algorithms, Probabilistic Algorithms, Immune Algorithms, Neural Algorithms, Fuzzy logic Algorithm. Among them researchers are using single algorithm method and sometimes hybrid of two or three single methods. Evolutionary methods are inspired by organic evolution like mutation, recombination etc. Among the evolutionary methods Genetic Algorithm (GA), Differential Evolution (DE), Genetic Programming (GP) are very prominent techniques used by several researchers [11]. Moreover. Stochastic Algorithms problems deals with random variables formulation involving random fitness functions with constraints [12].

The inspiration of Swarm Intelligence (SI) algorithms comes from nature, especially biological organisms. Present days optimization strategies revolves around this swarm intelligence methods like Particle Swarm Optimization (PSO), Ant Colony Optimization (ACO), and Artificial Bee Colony (ABC) etc. Physics-related algorithms consists of Gravitational Search Algorithm (GSA), Harmony Search (HS), and Simulated Annealing (SA) etc. [13]. Biswas et al. reviewed different Physics-Inspired Optimization Algorithms [14]. Major areas studied by these methods are quantum concept, electrostatics, electro-magnetism, Newton's gravitational law, and laws of motion. Probabilistic Al-

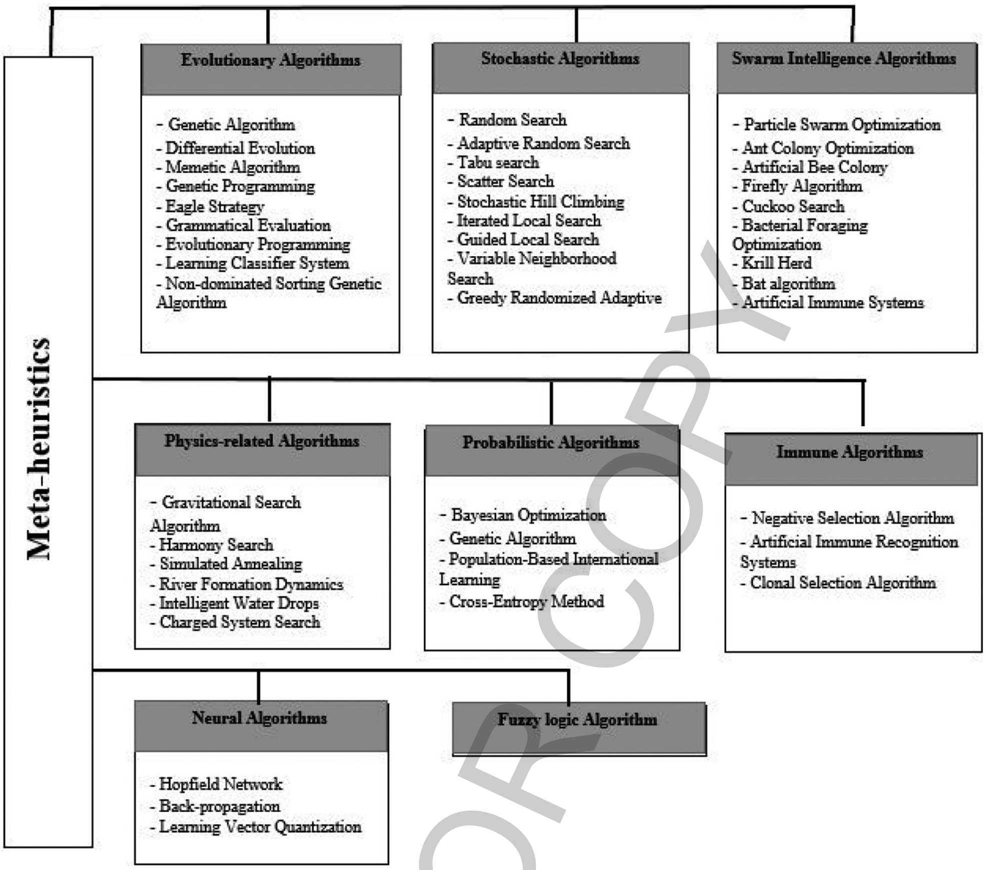

Fig. 1. Classifications of metaheuristics.

gorithms relies on the random input and have a chance to produce false result. Bayesian Optimization [15] is a kind of probabilistic algorithm. Immune algorithms are inspired by values and procedures of the vertebrate immune system [16]. Now-a-days researchers also use Neural Algorithms and Fuzzy logic Algorithm [17] for solving different optimization problems considering more than one uncertainty. Moreover, multi-objective metaheuristics are one of the current trends involving more than one fitness function to be enhanced simultaneously. Classifications of Metaheuristic Optimization [18] are shown in Fig. 1.

5. PHEV optimization problems and solution approaches

Now-a-days, the research academics are trying to minimize some parameters such as installation or operating costs, life-cycle budget of charging station, charging infrastructures burden and to maximize the average SoC, overall revenue, RESs integration etc. Moreover, intelligent monitoring of power allocation, real-time simulation and smart charging strategies has drawn much consideration to the research community [19].

Researchers have developed different mathematical models and end up with respective objective functions to solve the above mention problems related to PHEVs. Some of the PHEV optimization objective functions with mathematical models and system constraints are described below.

One famous model is *PHEV Markov chain model* [20] with the following principles:

(1) The charging of PHEV is done only at household and not fully charged.
(2) The PHEV power consumption is proportional to its time away until the state of charge (SOC) touches the minimum value.

The state of charge of the battery is given by $SOC(t)$ at time t. When fully charged the state of charge is at a maximum level $SOC(t) = SoC_{\max}$. With time-step Δt this can be expressed via the following equation:

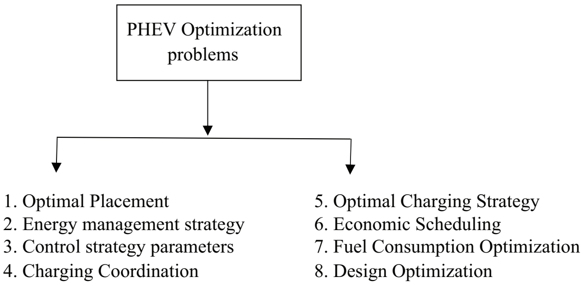

Fig. 2. PHEV optimization problems.

$$\begin{aligned} &SoC(t+\Delta t)\\ &= SoC(t) - C^{EV} S(t)\Delta t \text{ if consuming},\\ &= SoC(t) + C^{Charge}\Delta t \text{ if charging},\\ &= SoC(t) \text{ otherwise}, \end{aligned} \tag{1}$$

Here, the state of charge, $SoC(t)$ is linearly decreased with an electricity consumption of C^{EV} times the seasonal coefficient $S(t)$. The PHEV is charged with charging power C^{Charge}.

The system constraint can be stated as follows:

$$SoC_{\min} < SoC(t) \leqslant SoC_{\max} \tag{2}$$

Another common model is *PHEV probability distribution model* [21]. This model was based on Bernoulli probability distributions and a maximally opportunistic charging scheme; charging every time the vehicle stopped.

The model is described by the probability of charging or not charging, this means that the electricity use Q could be modeled by a stochastic variable $X \sim Bernoulli(p)$ with a weight for power use C^{Charge}.

$$Q = C^{Charge} X \tag{3}$$

Moreover, the complete *model for PHEV grid interaction* can be formulated [22] as below:

$$P(t) = P_{PV}(t) - P_{Household}(t) - P_{PHEV}(t) \tag{4}$$

Where $P(t) = PHEV$ home charging power consumption over time t; $P_{PV}(t) =$ The power consumption/production at the end-user in the grid for the individual household level with *PV* power production over time t; $P_{Household}(t) =$ Household power consumption over time t; $P_{PHEV}(t) = PHEV$ home-charging power consumption over time t.

Various optimization problems related to PHEV research are described in this section and stated in Fig. 2.

5.1. Optimal placement

Many metaheuristic techniques have been suggested to solve the optimal placement problems of PHEVs under a steady-state situation. Different fitness functions as well as constraints have been presented in different optimization methods to reduce device cost and alleviate certain power quality instabilities such as sag of voltage and harmonic distortion [23]. Authors [24] propose multi-objective optimization method to improve the voltage profile, minimize the voltage total harmonic distortion, and reduce the total investment cost. They compared Dynamic Discrete Firefly Algorithm (DDFA) with the conventional Stationary Firefly Algorithm (SFA), Hybrid Improved Genetic Algorithm (HIGA), and Dynamic Particle Swarm Optimization (DPSO) and showed the ability as well as accuracy of DDFA over others.

Authors [25] apply Genetic Algorithm (GA) for designing the efficient grid-friendly parking lot of PHEVs. The results specify a decrease in real power losses and development in the voltage profile through the distribution line. The suggested algorithm performs sensibly in allocating the lesser charging rate standards while there are higher arrival rates and higher (on-peak) time-variable total load values. Hajimiragha et al. [26] inspected the optimal deployment of the electric grid structure during off-peak periods for charging PHEVs. Authors use Robust Optimization Approach to realize the viability of PHEVs considering the most appropriate planning uncertainties. Optimal Routing and Scheduling of PHEVs were performed by Barco et al. [27] using Differential Evolution (DE) method. Author's methodology considers the search of optimal routes and the minimization of operation costs. Rahman et al. [28] apply Gravitational Search Algorithm (GSA) for smart energy allocation in PHEV charging infrastructures. Authors also compare the result with particle swarm optimization (PSO), considering constraints such as energy price, remaining battery capacity, and remaining charging time.

5.2. Energy management strategy

Energy management of PHEVs is a vital issue for proper operation of electric vehicles. The most commonly used energy storage system is battery. Other storage systems are: flywheel, Ultra capacitor (UC), hydrogen tank etc. The main aim of effective energy management is to increase the fuel efficiency without deteriorating the vehicle performance [29]. Chen et al. [30] use genetic algorithm (GA) to optimize power threshold based on PHEV fuel-rate, state of charge (SoC) and driveline power demand. The optimum battery current during engine on condition is calculated using quadratic programming (QP) method. Numerical simulations validates the effectiveness of the proposed methods. Authors [31] use Genetic-based bacteria foraging algorithm (GABFO) to optimize energy management of hybrid electric vehicles. Simulation results display the reduction in fuel consumption, whereas retaining technical and commercial efficiency of the electric vehicle. Zhang et al. [32] use Fuzzy logic control in electric vehicle simulation software platform ADVISOR for energy management.

5.3. Control strategy parameters

Several researchers are trying to enhance the control strategy parameters hence optimize the overall performance of PHEVs.

Rousseau et al. [33] use a Non-derivative based algorithm, DIRECT to optimize the major parameters of a pre-defined control strategy algorithm. The results demonstrate the need to have different control parameters depending on distance and drive cycle. An Optimized EV Charging Model Considering TOU Price and SOC Curve is proposed by Yijia et al. [34]. Simulation Results indicate that the improved charging configuration has immense benefit in decreasing the cost and flatting the load curve. Authors [35] apply Simulated Annealing (SA) algorithm to optimize the operational parameters of a series hybrid EV hence reduce consumption of fuel. Authors consider State-of-Charge (SoC) of the battery, Motor and Generator as control parameters. Tian et al. [36] propose parallel HEV fuzzy control strategy based on Chinese urban driving cycle for improving the fuel consumption and reducing emissions. Authors also used GA to improve the parameters of fuzzy controller. Results show that, the fuzzy control strategy could improve the overall fuel consumption and minimize emissions efficiency. Authors [37] used GA to optimize powertrain parameters hence reduce fuel consumption. Moreover, Fung [38] use Multi-objective GA (MOGA) to solve the Pareto-optimal solutions set and enhance HEV performance in terms of fuel economy and emissions, and ensure user satisfaction with driving performance.

5.4. Charging coordination

Most distributed and important energy resources like wind energy and photovoltaic panels have arbitrary and irregular in nature. Implementation of strategic charging coordination will enhance the overall energy sources performance of PHEVs. So, Proper and effective researches on this charging management and effective utilization is underway.

Authors [39] use Ant Colony Optimization (ACO) for transformer side charging synchronization of PHEVs. Simulation results relate and compare the load charging curve of PHEV with the effect of load fluctuation. Ning et al. [40] propose an intelligent charging algorithm for electric vehicle charging services in reaction to TOU price. The aim is to improve the stress in power grid under peak demand and to meet the demand response requirements in regulated market. Moreover, authors [41] introduce a centralized scheduling policy for PHEV charging using genetic algorithm (GA) to facilitate the size and complexity of the optimization.

Proper charging coordination is necessary for upcoming PHEV penetration in the vehicular network. There exists 'Rang anxiety' among the owners of PHEVs which refers to become worry about the electric vehicle mileage because the on-board storage needs to be charged when the state-of-charge reaches a certain limit [42]. Uncoordinated fashioned PHEV charging is the source of disturbances to the power grid; i.e. lines and transformers overload and voltage drops [43].

5.5. Optimal charging strategy

One of the most recent charging strategies of PHEVs is smart charging. The awareness behind smart charging is to give charge to the PHEV when it is most advantageous, which could be when electricity price, demand is lowest, when there is excess capacity [44]. Ahmad et al. [45] propose a smart charging algorithm namely SOC-based charging using Evolutionary Programming (EP) to find out the optimal charging rate, state-of-charge and lowest cost for charging. Results gain from the study show that rate of charging, load level and initial SoC have important impact on charging cost per day. Authors [46] use Artificial Immune System (AIS) and Tangent Vector (TV) technique for PHEV recharging policy of IEEE 34-bus distribution system. Results of the TV-based optimization method allow a substantial loss reduction with a lesser computational complexity. But authors avoid simulation for larger distribution systems.

Niklas et al. [47] use Dynamic programming (DP) for optimal control of charge in deregulated electricity markets. Authors do Net Present Value (NPV) comparison among different charging algorithms of PHEVs and conventional ICEVs. The obtained cost curves shape is very sensitive with respect to the lowest price of the day. Authors [48] do a tradeoff between power management strategy of stochastic optimal PHEV and electro chemistry-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. Sundstrom et al. [49] apply two optimization methods named Liner Approximation (LA) and Quadratic Approximation (QA) to optimize PHEVs charging behavior with the aim of reducing costs of charging, achieving desired SoC, and optimum balance of power. Simulation results prove that the linear approximation is sufficient for charging plan optimization. Rahman et al. [50] use Hybrid PSOGSA (Particle Swarm Optimization and Gravitational Search Algorithm) for state-of-charge (SoC) maximization of PHEVs hence optimize the overall smart charging.

5.6. Economic scheduling

Economic scheduling is an area where less attention has given by the researchers in optimization field. Integration of renewable energy sources is a challenge for upcoming smart grid technologies. Most of the renewable energy sources such as solar and wind rely considerably on factors like weather. For this, energy produced by renewable sources tends to be intermittent in nature with the characteristics like short time fluctuation. The on-board battery of electric vehicle shows a noteworthy part in decreasing this fluctuation of alternative production of energy [51]. The smart grid concept deals with the uncertainty of renewable energy production by scheduling the PHEVs according to the availability of renewable energy resources. During the pick time of electricity demand, the PHEV can be charged from renewable energy-based charging infrastructure hence optimize power production from the traditional grid. According to Sojoudi and Low [52], "The scheduling problem for the PHEV charging can be augmented into the optimal power flow (OPF) problem to obtain a joint OPF-charging (dynamic) optimization". They prove that the duality gap is zero for the joint OPF-charging optimization if it is zero for the classical OPF problem using IEEE 14 bus system.

5.7. Design optimization

Numerous design studies have been undertaken for hybrid electric vehicles and plug-in hybrid electric vehicles in the last few years. In [53] it is evidently recognized that the consumption of energy by a PHEV is powerfully related to the powertrain components size. Zhang et al. [54] apply and compare chaotic sinusoidal pulse width modulation (SPWM) and the chaotic space-vector pulse width modulation (SVPWM) for motor drives in EV and computational simulation is carried out by Simulink software. For the control algorithm, the chaotic SPWM algorithm shows less computation complexity than the chaotic SVPWM algorithm. Authors [55] use Particle Swarm Optimization (PSO) approach for optimal sizing PHEV powertrain components such as storage system, electric motor, engine power. Simulation results show that the optimized vehicle components using PSO consequences advanced operation performance and more fuel savings.

Patil et al. [56] perform Sequential Quadratic Programming (SQP) method to optimize the design of a series PHEV powertrain for preferred All Electric Range (AER) considering real-world driving scenarios. The method employs Markov chains to produce synthetic drive cycles characteristic of real-world driving. Huang et al. [57] perform linear programming (LP) method to make optimized storage schedule and power trading decisions. The power market trading is used when the intermittent renewable energy is unavailable and the extra power will be retail back to market to cut the cost of electricity.

5.8. Fuel consumption optimization

It is important that the automotive industry comes up with new solution techniques due to the necessity of lesser fuel consumption and emissions. Proper and efficient fuel consumption will take PHEV to one step forward to avoid using traditional fuel sources. As PHEV runs on both fuels and electrical charging, so lowering the fuel consumption will be an attractive field of research in electric vehicle domain. Plug-in Hybrid Electric Vehicles (PHEVs) are gaining establishment as an environment friendly alternative to traditional vehicle and playing an essential role in boosting up the overall fuel efficiency. Authors [58] apply a new hybrid metaheuristic optimization algorithm named PSAGADO (Particle Swarm And Genetic Algorithm with Downhill-simplex Optimization) to minimize fuel consumption over a given driving cycle. Results shows about five percent superiority of this method compared to standard optimization strategies for the reduction of fuel consumption. After that, surface-fitting method is applied to improve best solution of PSO method.

Fig. 3. Applying metaheuristic optimization algorithms with various PHEV mathematical model. (Colours are visible in the online version of the article; http://dx.doi.org/10.3233/IDT-150245)

Fei et al. [59] use simulated annealing, adaptive based hybrid genetic algorithm (SAAHGA) in order to minimize the fuel consumption and maintain driving performance. The results justifies the use of hybrid optimization method. In [60,61] optimization techniques such as Dynamic Programming (DP) and convex optimization are used to PHEV models and the authors declare that the considered search space is highly non-linear with non-continuous areas. Battery capacity, charging location, charging rate and duration, vehicle types have significant impact on fuel consumption. So, these constraints should be carefully handled in order to perform fuel consumption optimization. The Fig. 3 shows the connection of metaheuristic optimization algorithms with various PHEV mathematical model.

Moreover, proper parameter settings are necessary in order to apply any particular metaheuristic optimization technique. In any computational experiments, it is important to document parameter settings in sufficient detail hence exact replication of experiments can be possible by the future researchers. Wasil et al. [62] suggest a system, based on statistical design of experiments and gradient descent that finds effective parameter settings found in metaheuristics. Authors propose four steps of parameter settings. In the initial step, a subset of problems from the entire set of problems should be selected in order to examine. In the next step, computational experience is needed for selecting the preliminary level of each parameter, the parameter range, and the amount to change each parameter. In the third step, authors select worthy parameter settings for each problem in the analysis set using statistical design of experiments and response surface optimization. In the fourth step, the parameter values obtained in the third step are averaged in order to obtain high-quality parameter values.

A summary of different metaheuristic strategies related to PHEVs optimization are presented in Table 1.

6. Advantages and disadvantages of the metaheuristics approaches

In the above sections, we reviewed the existing literatures on PHEVs optimization using various metaheuristic techniques. Every paper highlights the positive and negative impacts of their proposed optimization techniques. After reviewing those we conclude the following general advantages of using metaheuristics approaches:

6.1. Computational cost

For real life problems the computational cost of a full evaluation of the fitness function can easily become the dominant computational cost. This computational cost can have the effect of making the time for the metaheuristics to converge slowly [63,64]. Most of the metaheuristic methods used to optimize PHEV parameters have shown better result is terms of compu-

Table 1
Different metaheuristic strategies related to PHEVs optimization

Author (s)	Application	Metaheuristic optimization strategies
Farhoodnea et al. [24]	Optimal placement of PHEVs	DDFA, SFA, HIGA and DPSO [24]
Fazelpour et al. [25]		GA [25]
Hajimiragha et al. [26]		Robust optimization [26]
Barco et al. [27]		DE [27]
Rahman et al. [28]		GSA, PSO [28]
Chen et al. [30]	Energy management strategy	GA, QP [30]
Samanta et al. [31]		GABFO [31]
Zhang et al. [32]		ADVISOR [32]
Rousseau et al. [33]	Control strategy parameters	DIRECT [33]
Yijia et al. [34]		Optimization charge [34]
Wang et al. [35]		SA [35]
Tian et al. [36]		Fuzzy control, GA [36]
Salisa et al. [37]		GA [37]
Fang et al. [38]		MOGA [38]
Xu et al. [39]	Charging coordination	ACO [39]
Ning et al. [40]		Optimization charge [40]
Maigha and Crow [41]		GA [41]
Ahmad et al. [45]	Optimal charging strategy	EP [45]
Rorigues et al. [46]		AIS, TV [46]
Rotering and Ilic [47]		DP [47]
Bashash et al. [48]		NSGA [48]
Sundström and Binding [49]		LA, QA [49]
Rahman et al. [50]		Hybrid PSOGSA [50]
Sojoudi and Low [52]	Economic scheduling	DP [52]
Zhang et al. [54]	Design optimization	SPWM, SVPWM [54]
Yildiz et al. [55]		PSO [55]
Patil et al. [56]		SQP [56]
Huang et al. [57]		LP [57]
Krenek et al. [58]	Fuel consumption optimization	PSAGADO [58]
Zhiguo et al. [59]		SAAHGA [59]
Li [60]		DP [60]
Pourabdollah [61]		Covex optimization [61]

tational cost compared to other traditional techniques. The reason behind is that because of its simplicity, it is generally very fast and it is able to produce quite good solutions in a very short amount of computational time.

6.2. *Robustness*

The robustness of the algorithm is examined in terms of the variability of the final solutions from each set of experiments [65]. By tuning the parameters one can easily improve the robustness of metaheuristic optimization algorithms. Among the applied methods, swarm intelligence-based techniques showed better results in terms of robustness because of the proper exploration through the search space [66].

6.3. *Other advantages*

There are some other advantages found from previous literatures [67,68] such as:

(i) It is capable of escaping from a local optima.
(ii) Metaheuristic optimization algorithms are very useful where traditional methods get stuck at local minima.
(iii) Metaheuristics provide a very well-organized way of coping up with large complex difficulties.

6.4. *Disadvantages*

The few disadvantages of using metaheuristics approaches are given below:

(i) Metaheuristics need large number of parameters settings to be tuned compared to traditional methods [68].
(ii) There is no assurance that the best solution found will be the optimal solution [69].
(iii) Finally, metaheuristic methods are identified to struggle with certain strongly constrained mod-

els, although cutting-edge constraint handling techniques are available [70].

7. Future research directions

The next section proposes future research direction and measures for the metaheuristic optimization of PHEVs. This specific field of research is relatively fresh and probable future outlooks have to be emphasized, so that novel methods can be comprehended.

7.1 Technologists from multi-disciplinary fields should come forward to implement the theoretical knowledge. Researchers and engineers from diverse backgrounds like Control system, architecture, civil, mechanical and electrical engineering should play a vital role together in order to make PHEV integration in smart grid successful.

7.2 Charging infrastructure efficiency is a key performance indicator for successful penetration of PHEVs. Different sensors are needed for charging optimization and automatic detection of State-of-Charge (SoC). So, researches should design and construct metaheuristic techniques for this purpose.

7.3 Computational intelligence based techniques should be applied to solve numerous mathematical optimization problems in PHEV integrated smart electrical network. Proper parameter settings are needed for solving different non-linear objective functions [71,72]. Some future applicable algorithms are described below.

7.3.1 Cuckoo search (CS)

Cuckoo search algorithm (CSA) [73] is constructed on the brood parasitism of some cuckoo species. The algorithm practices the Levy flights instead of simple random walk. CSA uses the some basic guidelines which are stated below [74]:

i. Each cuckoo lays one egg at a time and dumps its egg in an arbitrarily selected nest.
ii. Merely the superlative nests packed of high-value eggs will undergo subsequent generation.
iii. The number of existing host nests is permanent. Moreover, the host bird determines the left egg by a cuckoo. In this circumstance, the host bird can either throw away the egg or simply give up the nest and construct a fresh nest.

Because CSA uses levy flights, so the method can be used for solving PHEVS complex problems. Levy flight shows better result than simple random walk.

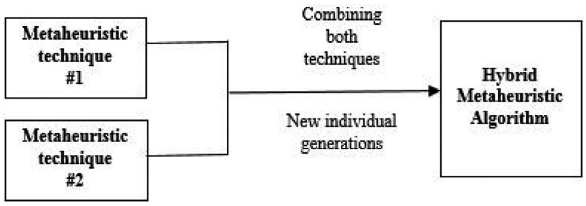

Fig. 4. Basic concept of hybridization.

7.3.2 Harmony search (HS)

Harmony Search (HS) [75,76] is a soft computing technique which derives from the improvisation process of musicians proposed by Zong in the year of 2001. The unique feature of HS is that it can handle both discrete as well as continuous variables [77]. Moreover, it may overcome the drawbacks of GA [78]. Most of the PHEVs optimization problems have been performed by using GA method. So, researchers should apply this new algorithm to optimize their fitness function.

7.3.3 Artificial bee colony (ABC) optimization

Artificial Bee Colony (ABC) algorithm is one of the most recently introduced swarm-based algorithms. ABC simulates the intelligent foraging behavior of a honeybee swarm [79,80]. There are three types of bees such as scouts, employed and onlookers. Generally, for each food source there assumed to be only one artificial employed bee. Moreover, the number of employed bees residing in a colony and the food sources number around the hive are same in number [81]. Future studies for solving smart charging problem of PHEVs should involve the ABC optimization technique.

7.4 Some of the research fields like smart parking lot optimization [82] and market participation strategy previously got little attention. So, researchers should pay attention to this issue.

7.5 Vehicle-to-Home (V2H) technology [83] is a new concept which allows the owner of PHEV to supply power to own home with its on-board energy storage (e.g. battery). Proper standardization is necessary with optimization constraints in order to adopt this newly emerged technology.

7.6 Plug-in Hybrid Vehicle business model [84] is another field of study where very less research work has done. Without proper business model it is impossible to implement several metaheuristic techniques within smart grid environment.

7.7 The storage system of PHEV is heavier than normal hybrid vehicle. Battery modelling and their effectiveness should be studied with the aspects of optimization algorithms.

7.8 Hybrid evolutionary swarm optimization
Hybrid metaheuristics are the latest addition in the field of optimization. In order to utilize the benefits of two or more single metaheuristic techniques, researchers are trying to combine them in order to get better results in terms of computation time and best fitness value. Blum et al. [85] provide a short survey on hybrid version of metaheuristics. In the field of PHEVs, only a few hybridization works have been done so far [28,47,55,56]. So, there is a huge gap in terms of Hybrid techniques in PHEVs. The main inspiration behind using the hybridization techniques of diverse techniques is to utilize the corresponding appeal of different optimization approaches, that is, hybrids are supposed to benefit from cooperation. Hybridization can be done with population-based metaheuristic with local search or other single techniques. The basic concept of hybridization is shown in Fig. 3.

There are different forms of metaheuristic technique hybridization [86–88]. The first one consists of combining components from one metaheuristic with another one. The second form concerns structures that are often categorized as cooperative search. They comprises of various algorithms swapping information in some mode. The third form is the integration of approximate and systematic (or complete) methods. These three hybridization techniques with examples are described below:

7.8.1 Component exchanging among metaheuristics

A standout amongst the most well-known methods for hybridization concerns the utilization of trajectory methods in population based strategies [89]. The greater part of the fruitful uses of EC and ACO make utilization of local search methodology. The explanation behind that gets to be evident when breaking down the separate qualities of trajectory methods and population based strategies. Population based strategies are better in distinguishing promising areas in the search space whereas trajectory methods are better in investigating promising areas in the search space [90].

7.8.2 Cooperative search method

Cooperative search receives more attention very recently, which is among other reasons due to the expanding research on parallel implementations of metaheuristics [91]. The goal of research on parallelization of metaheuristics are mainly two points. Firstly, metaheuristics should be reformed to make them appropriate for parallel implementation in order to exploit intrinsic parallelism. Secondly, a genuine blend of metaheuristics has to be found, both to combine diverse characteristics and strengths and to plan well-organized communication mechanisms. Crainic et al. [92] survey the parallel implementations of metaheuristics.

7.8.3 Integration of metaheuristic and systematic methods

Integrating metaheuristic with Systematic Methods recently created very efficient algorithms particularly when applied to real-world problems [93]. A very fruitful example of such an integration is the combination of metaheuristics and Constraint Programming (CP) [94–96].

7.9 Hyper-heuristics optimization
The newest edition in the modern search capability-based metaheuristic research is hyper-heuristics optimization. The word ‘hyper-heuristics’ was first introduced in 2001 by Cowling et al. [97]. Hyper-heuristics are largely concerned with intelligently choosing the right heuristic or algorithm in a certain condition [98]. The crucial feature of hyper-heuristics is that they work on a heuristics search space rather than directly on a search space of problem solutions [99]. Current research trends and directions for future research in the domain of hyper-heuristics optimization are discussed [100,101]. For solving real-world problems of PHEV, this type of method should be applied and compared with other existing metaheuristics.

8. Discussions

Metaheuristics are powerful algorithmic approaches with great success to many complex problems in PHEVs. Our findings suggest a noteworthy awareness of motivation in metaheuristics applied to PHEV-related optimization problems since 2008. Genetic algorithm (GA) and Particle swarm optimization (PSO) are the most popular heuristic methods applied in different problems. It is also noticed that the usage of hybrid metaheuristics methods are increasing. For the future researchers, an extensive technical review emphasizing hybrid metaheuristic is suggested. Moreover, researchers should explore hyper-heuristic techniques and evaluate performance to solve various PHEV optimization problems. Matej et al. [102] offer some basic guidelines to conduct any replications and comparisons of evolutionary computation-based algorithms for optimization. Moreover, the comparisons conducted should be based on suitable performance measures and show the statistical significance of one approach over others. If the experiment is not replicated with sufficient care, any performance measures and statistical approaches cannot remedy the problems familiarized by inexact experiment replication. In other words, if collected data are grouped from experiments which exhibit large deviations the comparison is meaningless despite statistical test being applied [102]. 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. Finally, the algorithm codes should be publicly available in order to help the future researchers to replicate the previously applied algorithm for their comparison purposes.

9. Conclusion

An ever increasing number of PHEVs will significantly change the traditional views of the transportation industries, the social atmospheres as well as the commercial world. The transport electrification brings both opportunities and challenges to existing critical infrastructures. There are still significant amount of investigations needed before the full version of the electrification of transportation comes into reality. In this paper, various challenges and optimization issues of Plug-in Hybrid Electric Vehicle (PHEV) are surveyed in order to shed light on cutting edge metaheuristics research and their implementation to solve most recent problems in this field. The 'future research directions' section also suggests some technical measures necessary to be implemented in order to facilitate the metaheuristics for upcoming PHEVs fleet into the road transport network. Since the research community have some troubles in coding metaheuristic, object-oriented and user friendly software should be developed in order to simplify the electric vehicle research.

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Conflict of interests

The authors declare that there is no conflict of interests regarding the publication of this paper.

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