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Optimal Scheduling Methods to Integrate Plug-in Electric Vehicles with the Power System: A Review ⋆

Zhile Yang *, Kang Li *, Aoife Foley **, Cheng Zhang *

* *School of Electronics, Electrical Engineering and Computer Science, Queen's University Belfast, Belfast, BT9 5AH, United Kingdom (e-mail: {zyang07, kli, czhang07}@qub.ac.uk).*
** *School of Mechanical and Aerospace Engineering, Queen's University Belfast, Belfast, BT9 5AH, United Kingdom (e-mail: a.foley@qub.ac.uk)*

Abstract: The introduction of the Tesla in 2008 has demonstrated to the public of the potential of electric vehicles in terms of reducing fuel consumption and green-house gas from the transport sector. It has brought electric vehicles back into the spotlight worldwide at a moment when fossil fuel prices were reaching unexpected high due to increased demand and strong economic growth. The energy storage capabilities from of fleets of electric vehicles as well as the potentially random discharging and charging offers challenges to the grid in terms of operation and control. Optimal scheduling strategies are key to integrating large numbers of electric vehicles and the smart grid. In this paper, state-of-the-art optimization methods are reviewed on scheduling strategies for the grid integration with electric vehicles. The paper starts with a concise introduction to analytical charging strategies, followed by a review of a number of classical numerical optimization methods, including linear programming, non-linear programming, dynamic programming as well as some other means such as queuing theory. Meta-heuristic techniques are then discussed to deal with the complex, high-dimensional and multi-objective scheduling problem associated with stochastic charging and discharging of electric vehicles. Finally, future research directions are suggested.

Keywords: Plug-in electric vehicle; scheduling; optimization; integration; power system; heuristic methods

1. INTRODUCTION

It has been widely argued that the increase in green-house gas (GHG) emissions associated with anthropogenic activities has significant impact on the global warming. The magnitude and frequency of natural disasters every year due to the extreme weather conditions partially caused by the global warming show the imperative need to reduce the GHG emissions. Furthermore, the limited fossil fuel reserves such as coal, oil and gas impose significant constraints on global economic development, in addition to the environment concerns from burning these fossil fuels. All these challenges call for the development of new technologies to utilize renewable and emission-free energy resources as well as the need to improve energy efficiency.

Transport is one of the major contributors to GHG and pollutant emissions and one of the biggest fossil fuel users in the world (Ipakchi and Albuyeh (2009)). However, the successful commercialization of electrical vehicles (EVs) may change this. First invented in early nineteenth, EVs have a long development history. In recent years, the Tesla has achieved a technological breakthrough for technical integration with the Roadster and Model S. The high performance and environment-friendly characteristics of these models have attracted broad attention for EVs. A number of articles have detailed EV powertrains, battery types, and popular styles of EVs (Koyanagi and Uriu (1998); Chan and Wong (2004); Chan (2007)). From a grid perspective, EVs can be categorized into pure battery electric vehicles (BEV) and plug-in hybrid electric vehicles (PHEV). A BEV uses a rechargeable battery as the primary source of power, whereas a PHEV uses a battery and an internal combustion engine to extend the driving range of the vehicle. The driving range of BEVs and PHEVs normally depends on the battery, but in the case of PHEVs, it also depends on both the internal combustion engine. Typical battery energy capacities may range from less than $10kWh$ to over $80kWh$. Both are referred to as plug-in electric vehicles (PEVs) for the purpose of this research.

The popularity of the Tesla and other EVs such as the Nissan Leaf, Toyota Prius and the recent introduction of the BMW i3 indicates that the automobile industry is investing heavily in transport electrification and believes that there is a market and future in EVs. There are some technical issues predominantly associated with EV range because of battery capabilities. However, this is now the

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focus of intensive collaborative research and development by battery and automobile manufacturers and already battery performances have improved. Then, there are potential grid issues due to the stochastic charging (and discharging) of PEVs, which may lead to sharp unexpected spikes in power consumption resulting in a deterioration in power quality and in particularly congested grids-voltage deviation, power loss (Bradley and Frank (2009); Richardson (2013)) and even blackout.

Fleets of PEVs also have the potential to provide distributed energy storage and ancillary services to the grid in the form of vehicle to grid services (V2G). Thus, the grid and PEVs are complementary to manage energy storage and power dispatch (Kempton and Tomić (2005a,b)). With optimal scheduling, PEVs could function as distributed generation and energy storage, for demand response as well as smoothing the intermittency and unpredictability of renewable generation such as wind and wave. Thus V2G has the potential to support grid operation and management (Leemput et al. (2011); Su et al. (2012); Andreotti et al. (2012a,b); Bessa and Matos (2012); Foley et al. (2012)). However, to achieve V2G apart from the smart grid infrastructure and electric vehicle service infrastructure (EVSE) robust intelligent scheduling methods are necessary.

In this paper the state-of-the-art optimization methods are reviewed for scheduling the energy power flow, economic load dispatch as well as for electric vehicles grid integration. Some analytical charging strategies to charge the PEV during valley time are discussed in Section 2. Then, some traditional numerical optimization methods are reviewed in Section 3. Meta-heuristic algorithms approaches are then examined in detail and compared in Section 4. Finally, Section 5 concludes the paper and future work is suggested.

2. ANALYTICAL CHARGING STRATEGIES FOR INTEGRATING PEVS WITH POWER SYSTEMS

Optimal PEV charging strategies are key prerequisite for seamless integration with the power system. Researchers have analysed various profiles and proposed elementary methods to schedule PEV charging.

A PEV can require up to 85 kWh to charge a battery to full capacity to support a range of 300 miles. If a number of PEVs are charged simultaneously in a specific time, the load, composed by the original load and the additional PEV load will increase by up to 20 kWh (Teslamotors (2013)). However, if the original load decreases proactively while a number of PEVs are charging, the total load may not deviate significantly. Shao et al. (2009) proposed a method to manage the load profile by controlling the household load. In this method, the real-time load profile is kept monitored and the PEV charging load can be sensed once plug-in. Some non-critical but high consumer loads, like water heaters or clothes dryers, can be turned off by a center controller for a short time to reduce the base load, so as to support the PHV charge.

However, it is not easy to control a domestic load considering existing infrastructure and the behaviour of the user. It is helpful to differentiate the sharp load rise by separating the total power need into a longer charging period. For example, Vandael et al. (2011) proposed two methods, namely the reactive strategy and the proactive strategy. The reactive strategy first postpones the peak by turning off some chargers and accumulating the necessary charging capacity to assure the balance of load profile as long as possible, and then turn on all chargers before the deadline comes to ensure the battery being fully charged. The proactive strategy calculates the future capacity from the day-ahead load profile and averages charging scenario to avoid overloading. The previous method sees a shorter charging period but may cause a sharp rise during quick charging stage, while latter method averages the deviation risk but may cost more time.

The approaches by Shao et al. (2009) and Vandael et al. (2011) adopt fixed charging scenarios, which keeps constant power in the charging process. If the value of charging power can be controlled, the charging rate can be calculated as dividing the actual charging power by the maximum charging power. Strategist may also allocate variable charging rate for each of the PEVs to balance the aggregate load. Amoroso and Cappuccino (2011) proposed two methods to calculate charging rates. One is the maximum energy with priority, which sets the charging power as the maximum from all energy requests, and the other is called spread energy with priority, which calculates the rate by dividing the total required energy with the entire available time period.

It should be noted that analytical charging strategies still stay at the elementary stages. The results are quite coarse and cannot ensure the optimal scheduling results. Moreover, most analytical strategies are based on broad assumptions, for example that all PEVs could start charging simultaneously during a specific period of time, leading the strategy to be divorced from the reality. Finally, but not least, the above charging strategies mainly consider approaches in terms of avoiding overload, while key issues like energy efficiency, GHG emission, energy dispatching cost and other elements are not considered and optimized. To tackle these problems and to develop more intelligent strategies, mathematical optimization approaches are proposed (Hajimiragha et al. (2011); Acha et al. (2010); Zhao et al. (2012)).

3. CONVENTIONAL MATHEMATICS OPTIMIZATION METHODS

Optimization is an important technique and has been applied in most scientific field. There are numerous traditional numerical optimization methods available to solve the scheduling problems relating to the integration of PEVs. Some of them have already been implemented to investigate PEV charging including linear programming (LP) (Sundstrom and Binding (2010)), non-linear programming (NP) (Bazaraa et al. (2013)), dynamic programming (DP) (Han et al. (2010)) as well as some other approaches such as queuing theory.

3.1 Optimal objectives and constraints

Numerical optimization algorithms solve a problem by modelling the system subject to an objective function and constraints, then utilize mathematical means to search for

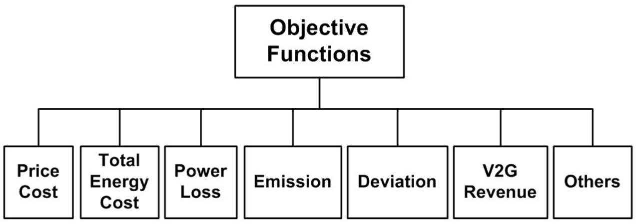

Fig. 1. Objective functions

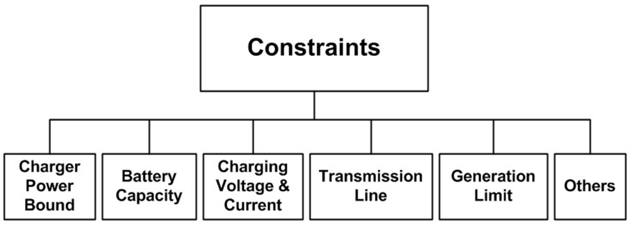

Fig. 2. Constraints

the best solution. Therefore, in order to develop optimal PEV scheduling strategies, the objective function and constraints should be formulated first.

Currently broad objective functions are proposed as those identified in Fig.1, which are based on minimizing the total tariff or price cost in order to save expenditure (Sundstrom and Binding (2010); Clement-Nyns et al. (2011)). The cost may include operation costs and fuel costs. From the power efficiency aspect, total Electricity costs as well as power losses are considered, aiming to schedule the power dispatch in a more efficient way (Clement-Nyns et al. (2010)). Environmental effects are also taken into account to reduce GHG emissions as well as some other gaseous pollutants such as nitrous oxied (NOx) (Hajimiragha et al. (2010)). For specific distribution zones, charging profiles may be presumed with an optimum and deviation variance minimizations are utilized so as to keep charging behaviour tracing the presumed optimal one (Sundstrom and Binding (2012)). For individual users, V2G revenue is the major incentive for them to join in the V2G service and thus the revenue is maximized to provide policy strategies for policy makers (Han et al. (2010, 2011)). Finally, other studies set the objectives based on other considerations, such as maximization of the average state of charge (SOC) (Su and Chow (2011)).

Constraints are introduced to bound the solutions within the physical and user-specified limitations. In Fig.2, infrastructure and facility constraints are proposed. Charger power, voltage and current are usually limited by PEV chargers and battery capacity. Generation and transmission constraints within the operating parameters of the grid operators 'grid code' are often considered for optimizing the whole distribution power system. Note that the solutions heavily rely on the mathematical methods, thus a number of numerical approaches have been used to tackle with the problems.

3.2 Linear programming

Linear programming, forming the problem with a first order polynomial and some equality/inequality linear constraints, offers a simple and effective optimization approach to model and solve problems with a low computation cost (Dantzig (1998)).

Basic LP formulates the objective functions as multiplying a known vector to an unknown variable. Sundstrom and Binding (2010) introduced basic LP to minimize price cost as

$$min\ f = t_s \mathbf{c}^T \mathbf{p}_b \tag{1}$$

subject to

$$\mathbf{A}_s \mathbf{p}_b \geq \mathbf{b}_s \tag{2}$$
$$\mathbf{A}_g \mathbf{p}_b \leq \mathbf{b}_g \tag{3}$$
$$\mathbf{A}_b \mathbf{p}_b \leq \mathbf{b}_b \tag{4}$$
$$\mathbf{b}_l \leq \mathbf{p}_b \leq \mathbf{b}_u \tag{5}$$

In the cost objective function, the charging power variable vector $\mathbf{p}_b$ was multiplied by a known cost vector c in (1). The linear constraints include inequality formulation with transmission constraint $(\mathbf{A}_s, \mathbf{b}_s)$ in (2), generation constraint $(\mathbf{A}_g, \mathbf{b}_g)$ in (3), battery constraint $(\mathbf{A}_b, \mathbf{b}_b)$ in (4) and the upper and lower bound $(\mathbf{b}_l, \mathbf{b}_u)$ in (5). Similarly, Clement-Nyns et al. (2011) formulated the objective function by basic LP with the tariff cost multiplied by the charging power, but the cost was simplified with two constant values for day-time and night-time instead of a cost vector.

For LP, the optimal solution is calculated with deterministic inputs. If some inputs have deviations or numerical errors, the results may not be accurate. Robust optimization is then introduced to utilize a certainty interval to indicate a value range of some uncertain input, thus may help to improve the robustness of the optimization process. Robust optimization can be combined with LP to deal with charge scheduling problems for PEV integration. Battistelli et al. (2012) integrated wind power and V2G service. The uncertainty of charging profiles of car parks (i.e. garages) was considered and was examined by uncertainty sets associated by a LP form. The robust optimization based LP (Bertsimas and Sim (2003)) was implemented to solve this problem.

Besides uncertainty, some inputs may be piecewise linear that the specific selected piece is decided by nominated integers. Hajimiragha et al. (2010) adopted mixed integer linear programming (MILP) to tackle a LP problem with a piecewise linearisation constraint. Its optimizing objectives include generation cost, environment credit along with emission cost for generation infrastructures and population areas. Hajimiragha et al. (2011) used both MILP and robust optimization. The piecewise linear generation emission inputs of three types of power plants were described by three sets of binary and auxiliary variables, forming a MILP problem, while the uncertainty of imports and export price input were modelled and solved by a robust optimization approach.

Though LP along with its variants is able to solve some elementary problems, the difficulty is that the simple framework cannot deal with complex non-linear systems with non-linear objectives goals such as deviation variance, thus it appear to be not robust to solve PEV charging optimization and other programming methods have to be used.

3.3 Non-linear programming

Non-linear programming can be used to deal with the objective function or constraints consisting of non-linear terms (Bazaraa et al. (2013)). Higher-order, non-negative functions, discontinuous objectives and some other forms of problems allow different approaches to model and solve respectively. Among them, quadratic programming (QP) has been used in developing PEV charging scheduling strategies. QP broadens the ranges of the objectives and enables some quadratic-form objectives to be formulated easily such as physical laws of power consumption and the deviation variance between the dispatching power variables and expected values.

Clement et.al formulated the power loss objective in a quadratic form in (6) and (7) based on the physical law (Clement et al. (2009); Clement-Nyns et al. (2010)) denoted as

$$min\ f = \sum_{t=1}^{t_{max}} \sum_{l=1}^{lines} R_l \cdot {I_{l,t}}^2 \tag{6}$$

$$s.t. \begin{cases} \forall t, \forall n \in \{nodes\} : 0 \leq P_{n,t} \leq P_{max} \\ \forall n \in \{nodes\} : \sum_{t=1}^{t_{max}} P_{n,t} \cdot \triangle t \cdot x_n = C_{max} \\ x_n \in \{0, 1\} \cdot \end{cases} \tag{7}$$

The charging process is based on a 4 kW power charger. $I_{l,t}$ denotes the current variable in the objective function where R_l is the equivalent resistor value of a transmission line. Battery capacity C_{max} and charging power limit P_{max} were formulated as constraints and x_n is the binary vector for deciding the existence of PEVs in a specific node.

Sometimes it is necessary to minimize the variance of certain objectives in strategy optimization, and the variance is the square of the deviation which is naturally in quadratic form. Some studies have implemented QP methods to solve this problem (Mets et al. (2010, 2011, 2012)). The key idea of designing the objective function in these studies is to minimize the variance of the deviation between the control power variable and the desired power value derived from the global profile. In Mets et al. (2010), the problem is formulated as

$$min\ f = \sum_{t=\alpha_i}^{\beta_i - 1} (L_{o,l}^i - L_1(t))^2 \tag{8}$$

$$s.t. \begin{cases} L_1^i(t) \leq L_{max}^i \\ C_c^i + \sum_{t=\alpha}^{\beta-1} L_c^i(t) \cdot \Delta = C_b^i \end{cases} \tag{9}$$

The minimization of variance is denoted by (8,9) in which the load variable is $L_1(t)$, and optimal load variables is $L_{o,l}$. The objective function is associated by the constraints of battery capacity C_b^i as well as load boundary L_{max}^i. Similarly, the minimization of variance has also been implemented in Zhang et al. (2012); Sortomme et al. (2011); Jian et al. (2013) to develop optimal strategy.

These forms only include one variable, but QP has also been used to optimize multi-variable quadratic functions. In Han et al. (2011), it defined the objective function to maximize the revenue gained by the aggregator based on the state of charge of PEV batteries. Two vectors, including the weights determining the ratio of charging/discharging as well as the delivered power are both taken as variables in forming the quadratic terms. Apart from QP, some other non-linear programming approaches have been proposed. For example, in Acha et al. (2009, 2010), the objective function is merged as an absolute value to minimize the power loss.

The objective functions and constraints in linear and non-linear programming are supposed to remain static or time-invariant. If the strategy has many steps or the process involves time varying inputs, aforementioned modelling and programming methods may fail to perform.

3.4 Dynamic programming

Dynamic programming was first proposed in 1952 by Richard Bellman (Bellman (1986)). It splits the whole optimization process into a series of timeslots and seeks the solutions in each time step, thus being practical and useful to model time-varying scenarios. It has also been used in optimizing the charging schedule of PEVs in order to solve problems in dynamic processes or with time-varying input parameters.

If PEV provides V2G service and gains profit from power feedback, individual users may be sensitive to the electricity changing price in order to maximize revenue. Han et al. (2010) proposed an optimal aggregator scheduling method to provide frequency regulation services for charging each vehicle. A DP approach was then introduced to form an integer optimal model to determine charging consequence step by step in hourly periods. Though the solution simply solves the question about when to charge or regulate to ensure a single PEV to be charged adequately and obtain the maximal revenue, without considering the whole grid or distributed system scenarios, it lays a fundamental concept on the dynamic process optimization of V2G service for PEV integration. Rotering and Ilic (2011) present two DP algorithms to reduce both energy and money costs and improve profit considering battery degradation based on the dynamic electricity market price for a single PEV.

Besides considering the dynamic price, other dynamic input parameters are also concerned. In Xu and Wong (2011), SOC was treated as the variable and the optimization objective o_t considering charging cost c_t, power loss l_t as well as the departure penalty g_t is formulated as

$$o_t(\mathbf{s}_t, \mathbf{r}_t) = c_t(\mathbf{r}_t) + \lambda_1 l_t(\mathbf{r}_t) + \lambda_2 g_t(s_t) \tag{10}$$

$$\pi^* = arg\min_{\pi} J_1^{\pi}(\mathbf{s}_1) = arg\min_{\pi} \sum_{k=1}^{T} o_k(\mathbf{s}_k, \pi_k(\mathbf{s}_k)) \cdot \tag{11}$$

Among the inputs, departure penalty g_t is the function of SOC variable $\mathbf{s}_k$ and keeping changing in each step J_t^{π} during the whole dynamic process π^*. An approximate DP method was introduced using the state aggregation and sub-state to reduce the dimension of state and control space denoted in (11).

Foster and Caramanis (2010) consider optimal strategies from a load aggregator's perspective rather than from the user's perspective. A stochastic dynamic programming scenario was proposed to develop a dynamic biding strategy to maximize the revenue. Time-varying parameters including the power demands and market price are determined with stochastic probability coefficients in every dynamic step. System dynamics of the PEV number in every timeslot was also formulated as the time-variant value in the constraints. An optimizing DP approach was introduced in Foster and Caramanis (2013) and the optimal dynamic biding strategy was studied in comparison with the paradigm which bids the price based on the day-ahead forecast.

Dynamic timeslots are basic computation units in DP process and different periods of timeslots could be used for corresponding optimizing purposes. Different from single length interval DP a three-level internals structure was proposed in Li et al. (2012). This hierarchical strategy consists of three levels and periods of dynamic process, which schedule the system based on three different intervals with one hour, one minute and real-time respectively for dispatching the wind energy and conventional generation, charging PEV following the dispatching power as well as regulating real-time frequency. The real-time performance and internal length sensitivity of corresponding objectives are considered by the three-level structure, based on which multiple goals can be achieved.

By solving problems in time intervals, DP approaches accept time-variant parameters and strategy periods, and thus are more flexible for power system scheduling. However, primary programming methods such as LP are still used in solving problem in each timeslot computation unit, therefore it shares similar drawbacks with conventional LP methods.

3.5 Other mathematical methods

Besides LP, DP, MILP, and QP optimization methods, game theory and queuing theory has also been used to optimal schedule PEV charging.

Game theory can analyse conflicts and help to make interactive decisions (Myerson (2013)). A formulation of Nash Equilibrium in game theory was introduced in Ma et al. (2010) to describe and balance the problem of decentralized charging control for a large population of PEVs. The negotiation principle may consider the benefit of both individual PEV populations and the goal of 'valley-filling' strategy.

In queueing theory, a model is constructed to predict the queue lengths and waiting times (Kleinrock (1975)), thus it is also useful to model the charging sequence in scheduling PEV charging. In Li and Zhang (2012), the whole scenario is simulated based on two aspects, namely the residential community and the charging stations respectively. Considering the limit of the possible PEV number, the model is utilised based on Monte Carlo simulation. A similar method is proposed in Turitsyn et al. (2010) to avoid the synchronization of EV charging start time.

Some other approaches have also been used. For example, in He et al. (2013), two modelling methods, namely a non-linear complementary system as well as a convex mathematical programming method, which considering equilibrium state of coupled networks and electricity price are first analysed. Both methods were then combined to formulate a public charging station allocation problem with complementarity constraints. The objective of the problem is to provide a solution to policy makers for better allocation. The problem was solved by an active-set algorithm proposed in Zhang et al. (2009) which used zero pre-assumption values to divide the problem into a normal non-linear programming as well as a binary knapsack problem.

3.6 Drawbacks of conventional optimization methods

Though numerous optimization methods have been used to solve the scheduling problem and most of them can be implemented with some powerful commercial software solvers such as CPLEX (Battistelli et al. (2012)) and GAMS (Sousa et al. (2012)), there are also some drawbacks.

Firstly, all these methods deal with single objective, while multi-objective problems widely exist. For instance, many papers discuss the strategies to achieve profit and high energy efficiency as well as to reduce GHG emissions or generation and transmission cost from the operator's or aggregator's side. Some other studies set goals for individual PEV owners to achieve the low price cost of electricity used and gain economical benefit from the V2G repaid scheme. Obviously, a dilemma lies between the interest of the aggregator and customer as both aim to maximize profit. Moreover, the profit and other price related objectives may also contradict with the battery degradation and environment impact. Therefore, multi-objectives modelling methods should be introduced into the scenario to balance the situation and find a trade-off for optimal scheduling. However, multi-objective problems can not be solved by current single objective mathematical solvers.

Secondly, it should not be ignored that some practical objectives are modelled with a set of intractable terms, which might be highly non-linear and non-convex, being hardly tackled by conventional programming methods. The formulations have to be simplified to meet the constraints and necessities of the programming methods. This may lead to the loss of accuracy and the failure of generalization of the models.

Finally, when dealing with complicated optimization problems, the computational complexity is a concern. It is often very sensitive for conventional approaches when the number of solution dimensions increase with the result that the model complexity increase (Sousa et al. (2012)). Even DP sees a 'dimension curse' referred to as the curse of dimensionality (Bellman (1961)). In order to find the optimum solution, the computational cost of the approach is dependent on the specific solving process and some methods need many computational hours to solve a complicated problem.

In summary, though a number of conventional optimization methods are available for solving the integration of PEVs with the grid, more comprehensive and complicated scenarios are still challenging the development of scheduling strategies. Algorithms which may, regardless of variant formulations of the objective function, tackle profiles with practical and complexity models efficiently are on demand.

4. META-HEURISTIC ALGORITHM APPROACHES

Meta-heuristic algorithms are powerful optimization tools. They are naturally immune to non-linear, non-convex and high-dimensional systems, and the computational cost can also be limited. Generally speaking, meta-heuristic algorithms could be categorized as trajectory-based methods and population-based methods. Trajectory-based methods, such as the hill-climbing (Skalak (1994)) and simulated annealing (SA) (Aarts and Korst (1988)), keep updating solutions instructed by certain probability based trajectory, while population-based methods utilize a population of solutions search for the optimum solution synergistically. Existing popular population-based methods include genetic algorithm (GA) (Goldberg and Holland (1988)), particle swarm optimization (PSO) (Kennedy (2010)), differential evolutionary (DE) (Storn and Price (1997)), harmony search (Geem et al. (2001)), ant colony optimization (ACO) (Dorigo (2006)), covariance matrix adaptation evolution strategy (CMA-ES) (Hansen and Ostermeier (2001)) and biogeography-based optimization (BBO) (Simon (2008)) etc.

4.1 Trajectory-based methods

A trajectory-based algorithm utilizes solutions to trace a path as the iterations continue (Yang (2010)). Among this category, the SA trial has been implemented and compared with conventional methods. Sousa et al. (2012) proposed a mixed-integer non-linear programming (MINLP) formulation for EV charging scheduling. The complicated formulation of objective functions considers the costs of generation sources, supplier energy acquisition as well as factors covering V2G discharge, the costs of non-supplied energy, excess generated energy, and demand response. GAMS_N, GAMS and SA were implemented respectively to compare the accuracy and efficiency of the results. The conclusion reveals that the SA approach leads to 3% more cost than the GAMS_N approach, but its computation time is less than one second comparing to the 5h calculation time spent by the latter method. Since the global search ability and convergence speed of trajectory-based algorithm rely highly on initialization of parameters such as cooling factor in SA, more powerful methods of this category could further be developed.

4.2 Population-based methods

Many meta-heuristic algorithms are based on a group of solutions categorised as population-based methods. In some early researches, GA was applied to the hybrid electric vehicle (HEV) energy flow management in Piccolo et al. (2001). Due to the higher efficiency and easier implementation, PSO is adopted by more applications.

The PSO was proposed based on the behaviour of particles in a swarm. It keeps updating the position of each particle using changing velocity which is adjusted by receiving information from the global and local best counterparts. In Su and Chow (2011), the objective function is to maximize the average SOC considering the energy cost, battery capacity and remaining charging time which is highly non-linear and hard to be solved by conventional approaches. An adaptive weight PSO based algorithm was proposed and compared with interior point method (IPM) and the GA methods. In Saber and Venayagamoorthy (2009a), binary PSO was utilized to optimize the generation emissions, while in (Hutson et al. (2008); Venayagamoorthy et al. (2009)), the same PSO variant was utilized to determine buying and selling electricity times to gain more profit. In Soares et al. (2012), three different PSO algorithms, namely EPSO (Miranda and Fonseca (2002)), NPSO (Selvakumar and Thanushkodi (2007)) and standard PSO were implemented and compared to optimize the objective function which considers the generation cost from the aggregator point of view.

Besides utilizing popular PSO variants, specially designed PSO variants have been proposed as well. In Saber and Venayagamoorthy (2009b), an integer PSO algorithm was compared with several other optimization approaches including integer-coded GA (ICGA) (Damousis et al. (2004)), Lagrangian relaxation and genetic algorithm (L-RGA) (Cheng et al. (2000)), genetic algorithm (GA), dynamic programming (DP), Lagrangian relaxation (LR) (Kazarlis et al. (1996)), evolutionary programming (EP) (Juste et al. (1999)), and hybrid particle swarm optimization (HPSO) (Ting et al. (2006)) to tackle the unit commitment problem combining EV load. The results show that if proper parameters are set, the PSO is able to find the optimal solution efficiently with least memory space regardless the dimension limitation. In Saber and Venayagamoorthy (2011), a weighing factor was introduced to adjust the weight accounting of cost and emission, thus improved flexibility in formulating the objectives compared with previously proposed methods. In Soares et al. (2011), a novel PSO variant, which changes particle weights in each iteration using a Gaussian mutation method, was proposed and shown to outperform GAMS. Wang et al. (2012) utilized two PSO variants to optimize non-linear parameters, namely the ordered weighted averaging PSO (WT-PSO) and the set point tuning PSO (SP-PSO) respectively. In Zhao et al. (2012) wind power integration was considered and a comprehensive objective function including the probability distribution of wind power and the behaviours of PEVs was proposed. An interior point based particle swarm optimization (IPPSO) was employed to solve the non-linear and non-convex problem.

Except for PSO, in Su and Chow (2012a,b), the estimation of distribution algorithm (EDA) was used in optimizing the PEV charging strategy in comparison with GA, PSO and IPM.

Meta-heuristic approaches are not only able to search the optimal solution for a single objective, but also can solve multi-objective problems. From the individual PEV user's perspective, a dilemma exists between the energy cost and battery degradation. In order to minimize the charging cost, the SOC should remain high at the beginning of the trip, while this may lead to a fast degradation of the battery, thus a multi-objective problem which use the 'pareto front method' was proposed and solved by the non-dominated sorting genetic algorithm II (NSGA-II) (Bashash et al. (2011a,b)). Moradijoz et al. (2013) studied a multi-objective optimal framework for EV parking lots allocation in the distribution network. The objective function consists of distribution system reliability, power losses as well as investment cost which are balanced using weighing coefficients. Two scenarios with different weighing coefficient values were studied and GA were used to search the optimal solution of multi-objective functions. The profit derived from the parking lot installation and voltage profile are both improved through GA optimization approach.

In summary, although a number of meta-heuristic algorithms have been applied for EV charging scheduling, the complex nature of the problem suggests that the application of other powerful methods, such as the Quantum-inspired PSO (Meng et al. (2010)), hybrid algorithms like GA-API (Ciornei and Kyriakides (2012)) and recently proposed algorithms such as the Biogeography-Based optimization (Bhattacharya and Chattopadhyay (2010)) and Teaching-learning based optimization (TLBO) (Niknam et al. (2012)) may be more effective.

5. CONCLUSION AND FUTURE WORK

It is clear that the integration of PEVs into power systems is a challenging topic, it affects many aspects of the power system, from the generation, transmission and distribution, to the economic dispatch and power flow optimization. Once scheduled and utilized properly, PEVs with distributed energy storage characteristics, may introduce significant contributions to enhance the power system efficiency and support renewable power integration. Further benefits such as minimizing the environment impact and maximizing the revenue of users may also be achieved through an optimal scheduling process.

This paper has reviewed the current state-of-the-art of PEV scheduling and optimization methods. Analytical charging strategies are concisely introduced, and traditional programming approaches are discussed. It was found that conventional optimization methods although can be quite efficient have some limitations for solving complex objective functions with constraints. Furthermore to solve multi-objective or high-dimension problems are even more challenging for these conventional approaches. Meta-heuristic algorithms are immune from these restrictions in principle. Their characteristics of high flexibility and efficiency offer distinctive merits in solving a complicated objective function combined with non-linear and non-convex problems associated with the PEV charging. A number of meta-heuristic approaches have been successfully applied to PEV charging scheduling, especially considering a suite of comprehensive and complex scheduling objectives regarding the integration of renewable energy.

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