

Optimization of Charge/Discharge Coordination to Satisfy Network Requirements Using Heuristic Algorithms in Vehicle-to-Grid Concept

Ahmet DOGAN, Serkan BAHCECI, Ferhat DALDABAN, Mustafa ALCI

Department of Electrical and Electronics Engineering, Erciyes University, 38039 Kayseri, Turkey

ahmetdogan@erciyes.edu.tr

Abstract—Electric Vehicles (EVs) have economic and environmental benefits for owner and the community. However, EV fleet charging may affect distribution network (DN) in negative manner. In order to overcome this problem, charging process should be coordinated well. If the charge coordination is inadequate to satisfy network standard, that can be provided by injecting power from some of the available EVs to grid. The concept, where EVs supply power to the network, is called Vehicle-to-Grid (V2G) and efficiency, reliability and stability of the network can be improved with V2G technology. Disadvantages of V2G concept are cost of coordination, infrastructure changes, battery degradation and disruption of EV owner comfort. In this paper, some most popular heuristic algorithms such as Genetic Algorithm (GA), Partical Swarm Optimization (PSO), Differential Evaluation (DE), and Artificial Bee Colony (ABC) are used in order to optimize the charge/discharge coordination in V2G concept. The optimization algorithms decide status of each EV to minimize the coordination cost considering network and EV constraints. Thus charging processes of EVs are affected as less as possible from coordination process. Results show that, all the given algorithms satisfy the network requirements and GA is the best in terms of optimization performance.

Index Terms—electric vehicles, genetic algorithms, heuristic algorithms, smart grids, optimization.

I. INTRODUCTION

Consumed energy at transportation sector is twenty five percent of the total consumed energy on the worldwide [1]. Therefore, fossil fuels consumption in transportation leads environmental pollution and high energy cost. Along with that, there is a growing sensitivity on energy efficiency and environment. Electric Vehicles (EVs) are the important options to reduce both fuel cost and green gas emissions. Therefore, many countries encourage people to purchase EV, and as a result, the number of EVs on the road is increasing day by day. According to the moderate scenario, it is estimated that 35% and 62% of total vehicles will be in hybrid or electric form by 2020 and 2050 in US, respectively [2]. In 2016, the number of open access charge points has reached 320.000 worldwide, growing by 72% since 2015 [3]. Such predictions and statistics promise a bright future for EV.

The smart grid, regarded as the next generation power grid, includes distributed energy sources, intelligent control and advanced communication technologies. It uses bidirectional flows of power and information to create a widely distributed automated energy delivery network [4]. EVs are

expected to be an important part of future smart grid with their opportunities as much as challenges. The main challenge is the huge loads from EV charging due to many of the EV owners arrive from work to home between 16.00 and 19.00 that corresponds the peak times for residential distribution network [5, 6]. If vehicles start charging as soon as they arrive home it causes such problems as increasing in peak load, overloading of transformers, degradation of voltage etc. [7-9]. That kind of problems can be solved with charge coordination. Moreover, EV can perform more than a load in smart grid due to its bidirectional power transfer feature once the required necessary infrastructure is established [10]. The ability of EVs to inject power into the grid is called Vehicle-To-Grid (V2G) technology [11, 12]. In this concept, EVs can be used as a generation resource as well as a storage device for certain periods of time to provide power to the grid.

The current situation of V2G technology, the impact on distribution network, challenges and opportunities are investigated in [10, 11]. V2G system consists of 6 main subsystems. In this structure, Energy Supply Provider (ESP) provides energy to customers through the distribution network (DN). Independent System Operator/ Regional Transmission Organization (ISO/RTO) provide the power system operation and control. Aggregator determines the charge/discharge status of EVs and provides an interface between EV, ESP and ISO/RTOs. Charging infrastructure, two way electrical power and communication, smart metering and control are other subsystems of V2G. As the penetration of EVs grows, auxiliary services such as frequency regulation, load shaving, spinning reserve, and voltage support can be provided by EVs [13-21].

In [22], optimization methodologies of charge/discharge are reviewed and numerical applications are carried out in [23]. Comprehensive objective function subject to constraints should be defined for optimal charging strategies. Objective functions are generally based on minimizing cost [24], power loss [13] and maximizing voltage profile [21], welfare [25], V2G revenue [26] etc. Constraints indicate the bounds of physical limit of system and EV owners' specifications. After defining objective function subject to constraint, optimization method is applied to reach best solution. Though numerous mathematical optimization methods such as linear programming [27], non-linear programming [28], dynamic programming [29], game theory [30] etc. have been used to solve the optimum charge/discharge problem, they have some draw-backs. Simplification may be required for

mathematical methods due to difficulties in solving highly non-linear and non-convex terms of objective function. This may lead to the loss of accuracy and non-optimum results. Also, mathematical methods cannot address the high dimension problem in a reasonable amount of time [31]. By contrast, heuristic algorithms naturally immune to non-linear, non-convex and high-dimensional systems, computational time can also be limited. Hence, heuristic algorithms are generally preferred for solving optimum charging coordination which is high dimensional and complex problem [32].

In [33], charging coordination of EV is provided using GA without peak load mitigation in their formulation. In [34], Particle Swarm Optimization approach is proposed in order to maximize EV owner income and mitigate power losses in distribution system. Peak load and network losses are decrease 9.76% and 2.62%, respectively. However, system voltage is not considered as constraints. In [35], Ant-based swarm algorithm is performed for charging coordination of EVs with load fluctuation and the transformer capacity constraints. While peak valley differences were 504.54 kW in free charging mode, it is decreased to 127.49 kW with charging coordination. However, EVs are not located in a distribution system. Hence, system losses and constraints are ignored in simulations. In [25], proposed algorithm aims to maximize the total utility considering EV charge demands. The method provides charging profits 3.4 times much more earned by the no-control strategy. However, only transformer capacity is taken into account as network constraints. In [36], Hybrid particle swarm optimization Gravitational Search Algorithm based optimization is used in order to optimally allocate power to each of the EVs. As increase in EV penetration, fitness value is increased from 144.838 to 183.094. However, no systems level realistic assessments have been performed.

In [37], Genetic Algorithm based solution is proposed for optimizing EV coordination in order to flatten load profile. However, the method does not guarantee fully charged battery at departure time. In [38], a heuristic algorithm is proposed to solve problem of scheduling EV charging with storage units. The aggregator's revenue can be improved by 80.1% using optimal charging scheduling. However, EV owners' benefits and EV constraints are not mentioned. In [39] and [40], EVs charging load is not considered individually, total load is assigned for system improvement. Hence, EV owner satisfaction is not provided. In [41], charging power of EVs in a fixed period is maximized. However, behavior of EV owner is not taken into account.

In [42], an EV charging coordination strategy is proposed with objective function of charging cost. Also system constraints are considered. In [43], Tabu Search algorithm is used to minimize the total operational costs of the distribution system. In [44], proposed method determines optimal schedule for the charging of each EV considering system requirements and individual EV owners. However, V2G strategy is not involved in [42-44].

On these bases, optimization unit should make optimal coordinated charge/discharge decisions in order to satisfy system constraints, meet power demand, maximize aggregator profit and owner comfort level. Nevertheless,

most papers fail to simulate EV coordination considering a distribution network or ignore some system constraints. Hence, system reliability is not guaranteed. Also, charging freedom has higher priority than financial income for EV owners in reality. Namely, delaying charging or discharging to grid negatively affects EV owners comfort. However, many of researches have deficiency in terms of EV owners satisfaction.

This paper addresses the charge/discharge coordination problem of EV for supporting system in a V2G concept. Our contributions are as follows;

- The methodology that considers, the uniform randomness of arrival and departure times, initial state of charge and EVs are located in IEEE-33 bus system to achieve realistic results.

- We proposed an objective function which minimizes cost of aggregator, guarantees maximum charging level of battery at departure time and satisfy network constraints in V2G systems simultaneously. Also, EV batteries reach to full as soon as possible. Hence, comfort level of EV owner is maximized.

- Swarm based (ABC, PSO) and evolutionary based (GA, DE) heuristic algorithms are used to solve optimum charge/discharge coordination and comparative results are presented.

II. PROBLEM FORMULATION

The increase in EV penetration will result in additional loads on the electricity grid. Moreover, simultaneous charging of all EVs causes violation in system limit. However, due to the V2G features, EVs can supply energy to distribution grid. The aggregator collects individual EV data and coordinates the EV charge/discharge based on ancillary service signal. Charge/discharge coordination problem is optimizing charge/discharge status of each EVs in order to obtain an economical operation of the distribution system and satisfying the system requirements of the system. Objective function of charge/discharge coordination can be technical or economical. In this work, objective function aims to minimize the cost which aggregator has to pay EV owner in order to provide system constraints. When the network constraints are violated, the aggregator decide status of each EVs to charge/discharge in order to reduce system load and improve system voltage. The charge/discharge tasks are assigned to EVs based on coordination cost. While control variables are charge/discharge status of EV, value of objective function depends on these variables.

The objective function $f(x)$ is cost of charge discharge coordination to be minimized. $\psi(x,u)$ defines power flow equations and $\varphi(x,u)$ indicates physical boundaries of the power system.

$$\text{Min. } f(x) \text{ subject to } \begin{cases} \psi(x,u) = 0 \\ \varphi(x,u) \leq 0 \end{cases} \quad (1)$$

Network standard is satisfied with optimization of charge/discharge coordination. State and control variables, constraints and objective function are formulated below.

State and control variables:

State variables of DN and EV are described as follows;

$$x(t) = \left\{ \begin{array}{l} P_{DN}(t), V_m(t), P_n(t), SOC_n(t) \\ n=1,2,..N, m=1,2,..M \end{array} \right\} \quad (2)$$

$P_{DN}(t)$ represents the total load of the DN at t . M is the total bus number of the network and each buses are indexed by $m=1,2,..M$. $V_m(t)$ denotes the voltage of bus m at t . N is the number of EVs connected to the network at t and each connected EV is indexed by $n=1,2,..N$. $SOC_n(t)$ is the state of charge of the EV battery at t .

Charge/discharge coordination requirement is decided for each t based on $x(t)$. Coordination is not required if the system is within limits. In case the network is out of the limit, first the charge coordination is applied. Charge coordination refers selection of EVs to stop charging process. If charge coordination fails to return to the network limits, then discharge coordination will be applied. Discharge coordination refers selection of EVs to be discharged. Status of each EV is considered as control variables at t as follows;

$$u(t) = \{u_n(t) | n=1,2,..N\} \quad (3)$$

where $u_n(t)$ is the control action on EV at t . $u_n(t)=1$ means EV n is allowed to charge. $u_n(t)=-1$ means EV n is assigned for discharge. If $u_n(t)=0$, EV n neither charges nor discharges. Naturally, The EVs, has not arrived yet, are not consider for charging or discharging options.

Network Constraints:

The total distribution network load $P_{DN}(t)$ includes $P_H(t)$ denotes total household load on the network, $P_{EV}(t)$ indicates total EV load and $P_L(t)$ represents losses on the network as shown in (4) and (5).

$$P_{DN}(t) = P_H(t) + P_{EV}(t) + P_L(t) \quad (4)$$

$$P_{EV}(t) = \sum_{n \in N} P_n(t) \quad (5)$$

Limit of P_{DN} which is decided by the generation capacity and the distribution transformer rating given as follows;

$$P_{DN}(t) < P_{DN}^{\max} \quad (6)$$

Limit of $V_m(t)$ given as follows;

$$V^{\min} < V_m(t) < V^{\max} \quad (7)$$

Electric Vehicle Constraints:

$E_n(t-1)$ denotes the energy of EV n at $(t-1)$, Δt is the minutes interval between t and $(t-1)$. $E_n^{\text{miss}}(t)$ and $T_{\text{req}}(t)$ calculates the amount of the missing energy and required time to reach maximum allowed capacity at t as represented in (8) and (9).

$$E_n^{\text{miss}}(t) = E_{\max} - \left(E_n(t-1) + \left(\frac{\Delta t \times P_n}{60} \right) \right) \quad (8)$$

$$T_{\text{req}}(t) = \frac{E_n^{\text{miss}} \times 60}{P} \quad (9)$$

$aet_n(t)$ is availability end time for charge/discharge coordination. t_n^{dep} is departure time of EV n and $aet_n(t)$ is calculated subtracting $T_{\text{req}}(t)$ from t_n^{dep} as given in (10).

$$aet_n(t) = t_n^{\text{dep}} - T_{\text{req}}(t) \quad (10)$$

The EVs only charge if the current time is equal or later than $aet_n(t)$ as given in (11).

$$\text{if } t \geq aet_n(t) \quad u_n(t) = 1 \quad (11)$$

Namely, EVs cannot be used for charge/discharge coordination later $aet_n(t)$. Otherwise, battery of the EV n would not be in maximum capacity at departure time. $aet_n(t)$ constraint is applied to ensure the maximum capacity of EV n at departure time. The EV users may provide a departure time or it can be estimated by probabilistic methods based on history of EV usage path [12].

Availability of EV n for charge/discharge coordination is also depending on user preferences and battery $SOC_n(t)$ which is the rate of current energy ($E_n(t)$) to energy capacity of EVs ($EC_n(t)$) as given in (12).

$$SOC_n(t) = \frac{E_n(t)}{EC_n(t)} \quad (12)$$

SOC_n^{\min} and SOC_n^{\max} , minimum and maximum limit of $SOC_n(t)$ as given in (13).

$$SOC_n^{\min} \leq SOC_n(t) \leq SOC_n^{\max} \quad (13)$$

In case of $SOC_n(t) \geq SOC_n^{\max}(t)$, EV n stop charge. Similarly, EV n is not available for discharging in case of $SOC_n(t) \leq SOC_n^{\min}(t)$.

Objective Function:

The cost of charge/discharge coordination is considered as the objective function $f(x)$ to be minimized as given in (14). Therefore the aggregator and EV owner are affected as less as possible from coordination process. $P_{n,dcc}(t)$, denotes the purchased discharge power from EV n and α_{dcc} is the cost of discharge per kW. Similarly, $P_{n,cc}(t)$ indicates the delayed charge power of EV n . α_{cc} and α_{dcc} are the costs of delayed charge and discharged power, respectively. ρ_{pen} , v_{pen} and aet_{pen} are penalty functions which occur in case of violation of maximum load, voltage and availability end time at t as presented (15), (16) and (17). c_{pen} is penalty coefficient.

$$f(x,t) = \left(\sum_{n=1}^N P_{n,dcc}(t) \right) * \alpha_{dcc} + \left(\sum_{n=1}^N P_{n,cc}(t) \right) * \alpha_{cc} \quad (14)$$

$$+ \rho_{pen}(t) + v_{pen}(t) + aet_{pen}(t)$$

$$\rho_{pen}(t) = (P_{DN}(t) - P_{DN}^{\max}) * c_{pen} \text{ if } P_{DN}(t) > P_{DN}^{\max} \quad (15)$$

$$v_{pen}(t) = \sum_{m=1}^M (V^{\min} - V_m(t)) * c_{pen} \text{ if } V_m(t) < V^{\min} \quad (16)$$

$$aet_{pen}(t) = \sum_{n=1}^N (t - aet_n(t)) * c_{pen} \text{ if } aet_n(t) < t \quad (17)$$

III. OPTIMIZATION OF EV CHARGE/DISCHARGE COORDINATION WITH HEURISTIC ALGORITHMS

Heuristic Algorithms are effective in solution of power systems due to ability of scanning wide range of solution quickly and approaching global optimum although the solution is generally reached locally optimum with classical methods [45]. Some optimization algorithms are presented for optimum coordination of charge/discharge process in the literature [46-48]. In this work, evolutionary and swarm based algorithms are used for EV selection in order to optimize charge/discharge coordination in the network structure of V2G. In Fig.1, flowchart of optimum charge/discharge coordination with heuristic algorithms is given. First, the charge/discharge coordination requirement is determined running Backward/Forward (B/F) Sweep power flow considering the voltage and maximum load limit in the system. Status of each available EV is determined randomly. If any violation occurs, penalty function is applied. Best solution is selected considering fitness values of solutions. The solution is updated using operators of algorithms in each iterations. Iteration is stopped when it reaches the maximum iteration number.

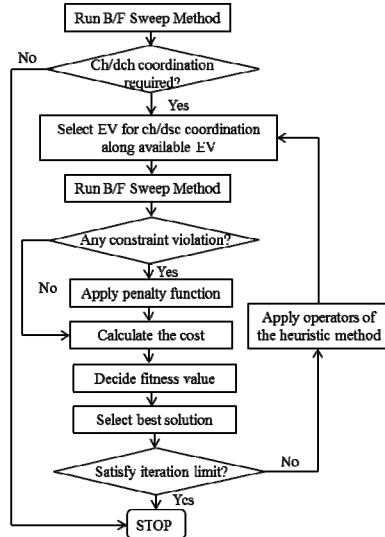


Figure 1. Flowchart of the optimization process of charge/discharge coordination with heuristic algorithms

Whereas chromosomes represent the potential solutions in GA and DE, quality of food sources and distance of the particle to the food represent potential solutions for ABC and PSO, respectively. In [49], new optimization criteria is defined that can be used of fuzzy controller with dynamics.

The solution vector of heuristic algorithms $X_i = (x_{i1}, x_{i2}, x_{ij}, \dots, x_{iD})$ corresponds to control variable vector $U = (u_{1,t_a}, \dots, u_{1,t_d}, \dots, u_{n,t_a}, \dots, u_{n,t_d}, \dots, u_{N,t_a}, \dots, u_{N,t_d})$ in EV charge/discharge coordination problem. Number of variables in the solution vector equals the number of control variable elements of U . mi is the total number of potential solution. i is the number of potential solution, $i=1,mi$. Each potential solution include D dimensional control variable vector. j is the number of parameter in variable

vector, $j=1\dots D$ [50, 51]. j th parameter of i th solution vector x_{ij} represent the charging action of EV n at t . Control variables vector which demonstrates the charging status of each EV for each time and it can be arranged as shown in (18). Therefore, the i th solution of heuristic algorithms has been encoded by a control variable. Number of rows equal to the dimension of the total number of aggregated EV (N) and a number of columns depend on the number of time interval between arrival (t_a) and departure (t_d) of the each EV. Although parameters are defined as a matrix in [52], control parameters are not mentioned in a matrix due to plug in durations of each EV is different here.

$$U = \begin{cases} u_1 = (u_{1,t_a}, \dots, u_{1,t_d}) \\ \vdots \\ u_n = (u_{n,t_a}, \dots, u_{n,t_d}) \\ \vdots \\ u_N = (u_{N,t_a}, \dots, u_{N,t_d}) \end{cases} \quad (18)$$

Each EV is indexed by $n=1,2,\dots,N$. When EV arrives the home and plugged in, SOC of EV read and departure is provided or it is estimated based on historic. The problem is solved and charge/discharge statuses of EV are updated for each time interval. The EVs charging schedule is generated between arrival and departure of EV [34]. $u_{n,t}^i$ is control parameter of n th EV in the t th time for i th solution. Value of $u_{n,t}^i$ defines the charging status of EV [5]. As mentioned detailed in Section-2, charging status can be 1, -1 and 0 expressing the charging, discharging and no action, respectively. The presented methodology finds the optimal charging schedule in order to solve EV charge/discharge coordination. The aggregator has to pay to EV owner for discharge and delayed charging process. Objective function is used to minimize cost of charge/discharge coordination. Charge and discharge times of EVs are decided using heuristic algorithms. While the cost of coordination minimizes, EV owner and system constraints are satisfied. Common process of the algorithms is similar but operators of each algorithms change solutions. In the algorithms, j th parameter of i th solution is initialized randomly considering upper and lower limits of the parameter as follows;

$$x_{i,j} = x_j^{\min} + rand(0,1)(x_j^{\max} - x_j^{\min}) \quad (19)$$

Best solution is selected considering their fitness values as follows;

$$p_i = \frac{fitness_i}{\sum_{i=1}^{mi} fitness_i} \quad (20)$$

The algorithms develop quality of solutions using their own unique operators which explained detailed under their headings.

A. Genetic Algorithm

New population is created using gene of chromosomes of previous population [53]. Best fitness of the chromosomes is

selected and transfer to next population. Firstly, chromosomes which refer the solution set are encoded. After random initialization, operator of reproduction, crossover and mutation are used. Chromosomes are selected from previous population for reproduction. Crossover refers gene changes between chromosomes as shown in Fig. 2.



Figure 2. Crossover process in GA

Mutation is random changing between genes of a chromosome as shown in Fig. 3. It creates individuals in the solution space but those are not in the population. Different mutation methods are available according to the coding types of individuals.



Figure 3. Mutation process in GA

Selection process is applied after genetic operators and the current population is updated with selected population.

B. Differential Evaluation

DE is a population based algorithm. Each chromosome is exposed to mutation, cross over and selection operators in order to create a new individual [54]. In mutation Donor vector ($v_{i,j}(t)$) is created by multiplying with scaling factor (F) difference of two chromosomes ($r1, r2$) and added to the third one ($r3$) as follows;

$$v_{i,j}(t+1) = x_{r1,j}(t) + F(x_{r2,j}(t) - x_{r3,j}(t)) \quad (21)$$

In cross over, the trial vector $U_i(t)$ is created mixing current vector $X_i(t)$ and donor vector $V_i(t)$ with Crossover Rate (CR).

$$u_{i,j}(t) = \begin{cases} v_{i,j}(t), & \text{if } \text{rand}[0,1] \leq CR \text{ } j = j_{\text{rand}}, \\ x_{i,j}(t), & \text{otherwise.} \end{cases} \quad (22)$$

In selection, the chromosome which has the highest fitness degree is transferred to the next generation regarding to comparison of $X_i(t)$ and trial vector $U_i(t)$.

$$X_i(t+1) = \begin{cases} U_i(t), & \text{if } f(U_i(t)) \leq f(X_i(t)), \\ X_i(t), & \text{otherwise.} \end{cases} \quad (23)$$

C. Particle Swarm Optimization

Searching for food of particles is simulated as searching solution for an optimization problem [55]. Fitness value of the particle refers its distance to food. Main operators are velocity and the position of the particle. Velocity of the i th particle updated as follows;

$$v_i^{(t+1)} = wv_i^{(t)} + c_1r_1(pbest_i - x_i^{(t)}) + c_2r_2(gbest - x_i^{(t)}) \quad (24)$$

where $pbest = (p_{i1}, p_{i2}, \dots, p_{iD})$ is best previous solution, and $gbest$ is best global solution in the memory. t is number of current generation, $r1, r2$ are uniform random value in the range $[0, 1]$, w is inertia weight factor, $c1, c2$ are acceleration constant of $pbest_i$ and $gbest_i$. Position of i th particle is updated summing its previous position and

current velocity as follows;

$$x_i^{t+1} = x_i^t + v_i^{t+1} \quad (25)$$

D. Artificial Bee Colony

A bee colony consists of three group bees; employed, onlookers and scouts [56]. Employed bee is on the food source in advance and it shares the quality of the source with onlookers bee. Onlookers bees select food sources considering source's nectar quality. Scouts scatter randomly to explore new food sources.

Producing new food sources: It is the operator of ABC. Neighborhood principle is considered by employed bees in order to decide the new food sources. Neighbors of quality food sources are selected as new sources as follows;

$$v_{i,j} = x_{i,j} + \phi_{i,j}(x_{i,j} - x_{k,j}) \quad (26)$$

v_i represents new food source. More quality sources have more probability to be selected.

IV. SIMULATION RESULTS

Optimization of charge/discharge coordination using heuristic methods are implemented on 33 bus residential distribution networks serving 1000 houses with nominal voltage of 12.66 kV and base power of 100 MVA. Houses are separated to 33 bus distribution network proportional with the load data of the network as given in APPENDIX A [57]. The load profile is generated in GridLAB-D which is developed by Pacific Northwest National Laboratory as a modeling and simulation tool of electric network [58, 59]. Load flow and optimization is simulated in MATLAB [60]. GridLAB-D allows detailed modelling of end use technologies based on users' behaviors and control of appliances. Multi-state appliances models were used to obtain realistic load profiles in house and distribution system. Total load profile of distribution system depends on many factors such as set points of thermostatic loads, output temperature, appliance usage frequency etc. In this study, simulated appliances are clothes washers, dishwashers, clothes dryers, refrigerators, plug loads, lighting loads HVAC units (heating, ventilating, and air conditioning), water heaters, and ranges [9, 61, 62]. House area is assumed to vary from 140 m² to 230 m². Meteorological data of Yakima, WA, USA is used as outdoor temperature and simulation is carried out in July. Cooling and heating set points of houses are selected between 21.1-23.8°C and 18.3-20.5°C, respectively. The set point of water heater is 48.8°C. Usage frequency of random pulsed appliances such as dryer, clothes washer dishwasher, range are varied by GridLAB-D based on calibrated End-Use Load and Consumer Assessment Program (ELCAP) residential load data [63]. The voltage magnitude at the substation was fixed at 1.0 p.u. (per unit). Maximum and minimum voltage magnitude limits are defined 1.00 p.u. and 0.9 p.u., respectively [64]. Load capacity is specified as 5000 kW. Three models of EVs placed randomly in 33 bus distribution network as given in APPENDIX A. Specifications of connected EVs are given in TABLE I. EV may be used for commuting or longer trips with higher capacity batteries. We considered daily commuting purpose and features of EVs were chosen to suit this purpose.

TABLE I. FEATURES OF EV IN 33 BUS DN

	EV1	EV2	EV3
Number of Connected EVs	131	104	165
Battery Capacity (kWh)	16.5	17	24
Charge/Disch. Power(kW)	1.9	3.0	3.3
Range (mile)	58.7	54.4	86.8

EV owners mostly departure from home between 06.00-09.00 and arrive home between 16.00-19.00. Hence, departure and arrival time distribution of EV created according to a normal probability distribution function with the mean at 07:30 and 17.30 of the variance of 1 h, respectively [65]. Daily average trip distance is 33 mile according to [66]. Trip distances of each EVs are calculated using probability distribution function with the mean at 33 mile of the variance of 4 mile. SOC_n^{arr} is battery state of charge at arrival time and calculated as follows;

$$SOC_n^{arr} = SOC_n^{max} - \left(dis_n \times \frac{range_n}{EC_n} \right) \quad (27)$$

SOC_n^{arr} depends on roundtrip distance (dis_n), range ($range_n$) and energy capacity of EV. Due to deep discharge and full charge decrease the battery life, EV n is allowed to be charged and discharged between SOC_n^{min} and SOC_n^{max} [67]. These are randomly selected as follow; $SOC_n^{max} = rand[0.9 - 0.99]$, $SOC_n^{min} = rand[0.3 - 0.4]$.

It is assumed that the aggregator has to pay 1.5 \$/kWh and 5 \$/kWh for delayed charging power and for discharged power to EV owner.

B/F Sweep method is used to perform a load flow analysis [68]. Line currents and bus voltages are calculated for each iteration to determine EV states to provide optimum charge/discharge coordination. At the initialization step, voltage of each bus assumed 1.0 p.u. and voltage deviations of buses are calculated. In the backward step, the currents are computed considering voltages of the previous iteration. In forward step, the node voltages are updated using voltage drops on the distribution network lines. The currents and voltages are updated iteratively until nodal voltage criterion satisfied.

Charge/discharge coordination is required when the DN constraints are violated. If the network does not turn to its limit although all EV stop charging, then discharge coordination is applied. Optimum charge/discharge coordination process determines the charge/discharge states of each EV to minimize the cost of coordination and disturbance of EV owners.

V2G system consists of three main components; grid, aggregator and EVs. There is a bidirectional communication and power flow between components. That can be foreseen to be available in the future smart grid. Also, smart meters play important role in order to send and receive data. The aggregator receives the support signal from operator, if the system limits are violated. Then, the aggregator of EVs starts to coordinate charge/discharge schedules to meet system requirements. Charging status of each plugged EV

are decided to minimize objective functions. Following consideration is assumed in the application:

- EVs have ability of bidirectional load flow and grid has the required infrastructure for communication between EV and aggregator.
- The EV coordination is controlled for each time interval which time period is divided into.
- Departure time of each EV is notified by user or it is estimated from historic driving patters.
- The EV owner permits the aggregator to determine charging status of EV.

In Fig. 4, EV load, DN load w/ and w/o EV are given. Uncoordinated charging process starts at 14.30 and finish around 24.00. Peak load is increased from 4760 kW to 5593 kW with integration of EVs at 18.00. Although total EV load is 748.5 kW, increase at total load is higher with increase of losses. Total load of the network is 4997 kW at 18.30. After that, total load is also lower than the maximum load limit of the network despite EV penetration.

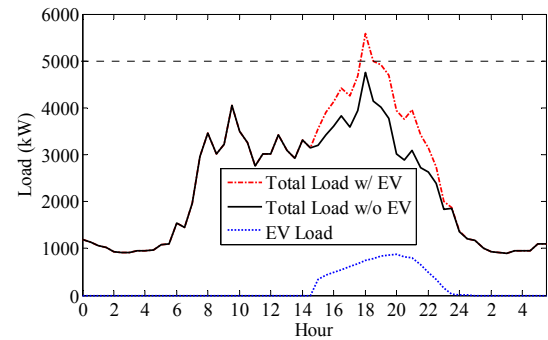


Figure 4. Total load and EV load of DN

In Fig. 5, minimum bus voltage magnitudes of DN are presented. The minimum bus voltage magnitude is lower than the 0.9 p.u. w/o EV penetration only at 18.00. That means, if all EV stopped charging process the network would be still out of limits. Therefore, discharge coordination of EV is required at that time. Because charge coordination is not adequate to satisfy network limits. On the other hand, minimum bus voltage decrease below 0.9 p.u. from 17.30 to 19.30 with the uncoordinated charging process of EV. Charging coordination is needed at those times except for 18.00.

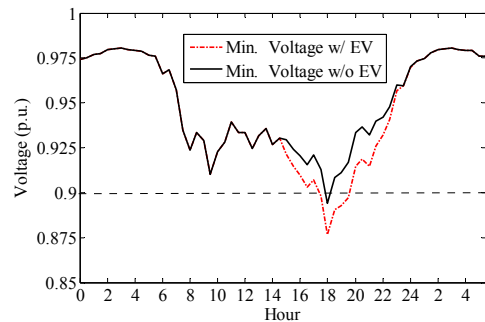


Figure 5. Voltage magnitude w/ and w/o EV

In Fig. 6, total network losses which highly increase with integration of EV are given. Total network losses increased from 300 kW to 383 kW at peak time.

In this paper optimization of charge/discharge coordination is provided using heuristic methods, GA, PSO, DE and ABC. The results of each algorithm are compared with each other. For each algorithm, population size and the

iteration numbers are selected 20 and 100, respectively.

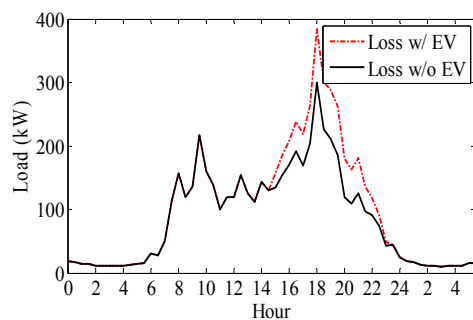


Figure 6. Losses of DN w/ and w/o EV

The best values of specific parameters of each algorithm are chosen based on experiment as follow;

PSO: $[w, c_1, c_2] = [0.5, 1.2, 1.5]$. w affects the search ability significantly but c_1 and c_2 decided the final values of position expectation and position variance. If w is selected too small, particles may not search sufficiently. Low values of c_1 and c_2 may lead particles to search far from target region before tugged back. High values of the weighting factors c_1 and c_2 may cause excessive motions or overshooting in the target region [69].

DE: $[(F), (CR)] = [0.6, 0.4]$. Small values of CR result in gradual and small exploratory moves in search space, while large values of CR produce rapid moves at angles to the search space's axes. Using too small a value of F leads to premature convergence, while high value high values slow down the search [70, 71].

ABC: Limit= [100]. Limit is the number of trials which bees to leave the food source. If limit is too low, sufficient search cannot be performed. If it is high, too much search is performed on one food source. Although time consumption is increased, the solution may not be increased [72].

GA: [Crossover, Mutation, Selection] = [Scatted, Constraint dependent, Roulette]

In Fig.7, Converge curves of the algorithms which are employed for charge coordination cost at 17.30 are shown due to network load and EV load level are same for each algorithm at that time. GA has the best results with \$0.014. Initialization value of GA is also better than other algorithms. Although, initialization values of PSO, DE, ABC are almost same, ABC has the highest value with \$0.089.

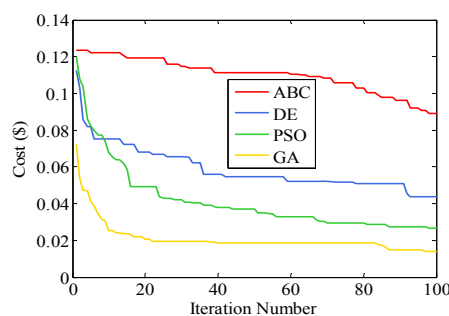


Figure 7. Coordination cost convergence curve at 17.30.

In Fig. 8, daily costs of the charge/discharge coordination process using heuristic algorithms are shown. Optimization of coordination process starts at 17.30 and finish at 19.30 for each algorithm. Charge/discharge coordination is not

required due to voltage and load of the network are within the limits at 20.00. Daily cost of coordination process are \$833.10, \$2871.90, \$3288.30, \$4169.10 using GA, PSO, DE, ABC, respectively. Cost of charge/discharge coordination changes depending on selected EV. Because connected bus of selected EV is significant for voltage support. Minimum cost is obtained using GA due to optimum selection of EV for coordination process.

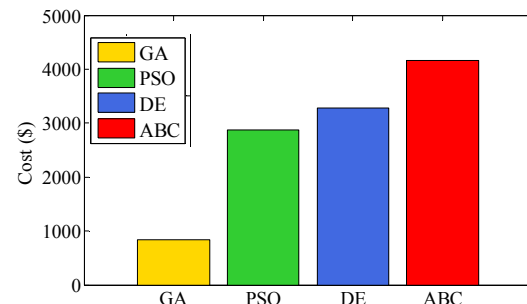


Figure 8. Daily cost of charge/discharge optimization

While the coordination process creates a cost for the aggregator, it also discomforts the EV owners by discharging or delaying charging process. Amount of discharged or delayed load are given in Fig. 9. V2G discharge period is shown in a box. Discharged powers are 93.5 kW, 146.1 kW, 180.8 kW, 254.2 kW using GA, PSO, DE and ABC at 18.00, respectively. EVs fully charged earlier with GA due to amount of delayed charging process is lower. Therefore number of charging EV is lower with GA at 19.30. Also, GA had the best convergence performance. Hence, delayed charging loads are 22.6 kW, 76.1 kW, 166.3 kW, 336.1 kW using GA, PSO, DE and ABC at 19.30, respectively. Delayed or injected load is absent at 20.00.

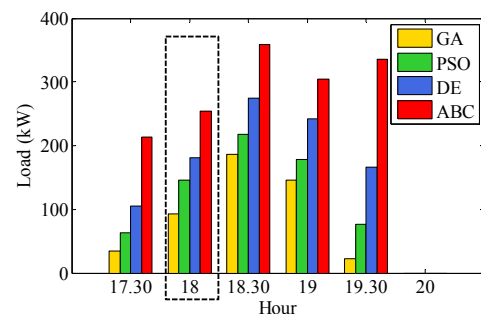


Figure 9. Delayed or injected load during coordination

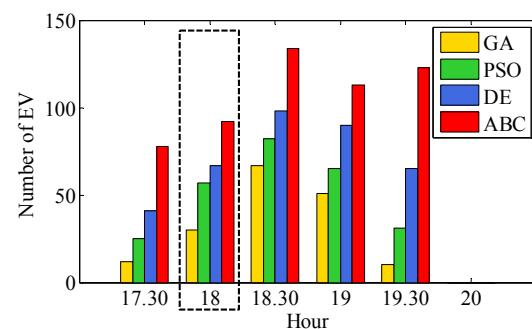


Figure 10. Number of EV that used for charge/discharge coordination

In Fig. 10, number of the EVs which affected from optimum charge/discharge coordination is presented. 12, 25, 41 and 78 EVs are selected to stop charging at 17.30 and 30, 57, 67, 92 EVs are selected for discharge at 18.00 by GA,

PSO, DE and ABC, respectively. GA presents the minimum number of selected EVs for coordination as well as the cost of coordination. The difference between algorithms is more evident at 19.30. While GA selects only 10 EVs, ABC selects 123 EVs to satisfy network requirement at 19.30.

In Fig. 11, total load of DN is presented for given hours. Total load of DN with GA is higher than others during charge/discharge coordination due to allowing using maximum capacity of the network. Total loads of DN are 4652.1 kW, 4595.6 kW, 4558.3 kW, 4479.7 kW using GA, PSO, DE and ABC at 18.00, respectively. However, total network load with GA is lower at 20.00 because of EVs which ended charging process before 20.00. Total loads of DN are 3948.7 kW, 4089.7 kW, 4136.8 kW, and 4184 kW using GA, PSO, DE and ABC at 20.00, respectively.

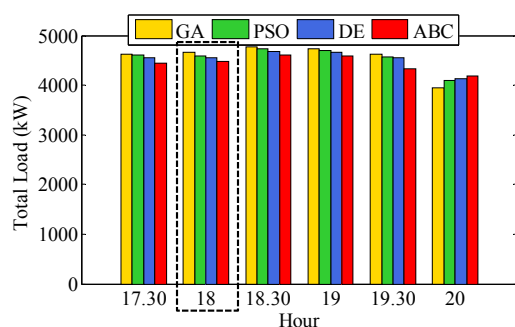


Figure 11. Total load of the DN

In Fig. 12, voltage values of each bus are given for 18.00. Minimum voltage magnitude w/o EV is lower than 0.9 p.u. only at 18.00. Therefore, discharge coordination is applied only at 18.00, while charge coordination is applied at other given times. Voltage magnitude is increased from 0.8768 p.u. to 0.9 p.u. with the given algorithms during discharge period.

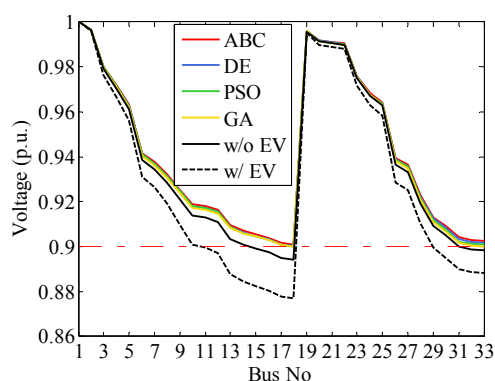


Figure 12. Voltage magnitude of each buses at 18.00

TABLE II. MINIMUM VOLTAGE MAGNITUDES WITH GA, PSO, DE, ABC

Minimum Bus Voltage (p.u.)						
Hour	w/o EV	w/ EV	GA	PSO	DE	ABC
17.30	0.9129	0.8980	0.9000	0.9001	0.9007	0.9023
18.00	0.8942	0.8768	0.9000	0.9001	0.9003	0.9008
18.30	0.9082	0.8907	0.9000	0.9001	0.9002	0.9000
19.00	0.9113	0.8929	0.9000	0.9010	0.9002	0.9000
19.30	0.9168	0.8971	0.9000	0.9003	0.9005	0.9039
20.00	0.9335	0.9149	-	-	-	-

Also, minimum voltage magnitudes are increased to minimum 0.9 p.u. with charging coordination at other given times as demonstrated in TABLE II. The coordination is not

required at 20.00 due to any of the bus voltages are not lower than 0.9 p.u. or total load of the system is not higher than 5000 kW.

V. CONCLUSION

The power consumption which is already continuously increasing stressed on network much more with the impact of charging EVs in peak hours. This leads to problems such as overloading, voltage drops etc. in distribution network. These problems can be solved by deferring charging and injecting power from EV using V2G feature in the smart grid infrastructure. However charge/discharge process should be well optimized considering system requirements, cost and comfort of EV owner. In this study, charge/discharge coordination cost is minimized to increase each bus voltage to EN50160 standards and reduce the total load below the maximum network load capacity using GA, PSO, DE and ABC. Also it is provided that EVs to be charged maximum at departure time. Therefore charging process and EV owner are affected as less as possible from coordination process. In case of comparison of the algorithms, GA provided both minimum cost and maximum convenience for EV owners. While the cost is minimized, network capacity is optimally used not to discomfort EV owner by reducing the number of selected vehicles for charge/discharge coordination. This allows both vehicles to be charged as quickly as possible, as well as longer average battery life due to minimizing number of switched EV.

REFERENCES

- [1] U.S. Energy Administration Office, International Energy Outlook, Washington, DC, USA, DOE/EIA-0484(2016), May 2016. [Online]. Available: [https://www.eia.gov/outlooks/ieo/pdf/0484\(2016\).pdf](https://www.eia.gov/outlooks/ieo/pdf/0484(2016).pdf)
- [2] Electric Power Research Institute, Environmental assessment of plug-in hybrid electric vehicles. Volume 1: Nationwide Greenhouse Gas Emissions, CA, USA, 1015325, July 2007. [Online]. Available: https://energy.gov/sites/prod/files/oeprdoc/DocumentsandMedia/EPRI-NRDC_PHEV_GHG_report.pdf
- [3] International Energy Agency. Global EV Outlook 2017 Two million and counting. Paris, FR, OECD/IEA 2017, July 2017. [Online]. Available: https://www.iea.org/media/topics/transport/Global_EV_Outlook_2017_Leaflet.pdf
- [4] X. Fang, S. Misra, G. Xue, and D. Yang, "Smart Grid – The New and Improved Power Grid: A Survey," IEEE Commun. Surveys Tuts., vol. 14, no. 4, pp. 944–980, 2012. doi:10.1109/SURV.2011.101911.00087
- [5] S. Xie, W. Zhong, K. Xie, R. Yu, and Y. Zhang, "Fair Energy Scheduling for Vehicle-to-Grid Networks Using Adaptive Dynamic Programming," IEEE Trans. Neural Netw. Learn. Syst., vol. 27, no. 8, pp. 1697–1707, 2016. doi:10.1109/TNNLS.2016.2526615
- [6] E. De Caluwé, Grid-supportive charging infrastructure for plug-in electric vehicles, PhD thesis, K.U.Leuven, – Faculty of Engineering Science, 2015. [Online]. Available: https://lirias.kuleuven.be/bitstream/123456789/511457/1/Phd_NLeemput_Final.pdf
- [7] J. Taylor, A. Maitra, M. Alexander, D. Brooks, and M. Duvall, "Evaluation of the impact of plug-in electric vehicle loading on distribution system operations," in Proc. IEEE Power Energy Soc. Gen. Meet., Calgary, Canada, 26–30 July 2009 pp. 1–6. doi:10.1109/PES.2009.5275317
- [8] M. J. Scott, M. K. Meyers, D. B. Elliott, W. M. Warwick, "Impacts Assessment of Plug-in Hybrid Vehicles on Electric Utilities and Regional US Power Grids Part 2: Economic Assessment," Pacific Northwest Nat. Lab., Richland, WA., DE-AC05-76RL01830, Nov. 2017. [Online]. Available: http://energyenvironment.pnl.gov/ei/pdf/PHEV_Economic_Analysis_Part2_Final.pdf
- [9] A. Dogan, M. Kuzlu, M. Pipattanasomporn, S. Rahman, and T. Yalcinoz, "Impact of EV charging strategies on peak demand

- reduction and load factor improvement," in Proc. Inter. Conf. on Elect. and Electronics Eng., Bursa, Turkey, 26-28 Nov. 2015, pp. 374-378. doi:10.1109/ELECO.2015.7394559
- [10] C. Guille and G. Gross, "A conceptual framework for the vehicle-to-grid (V2G) implementation," Energy Policy, vol. 37, no. 11, pp. 4379-4390, 2009. doi:10.1016/j.enpol.2009.05.053
- [11] M. Yilmaz and P. T. Krein, "Review of the impact of vehicle-to-grid technologies on distribution systems and utility interfaces," IEEE Trans. Power Electron., vol. 28, no. 12, pp. 5673-5689, Dec. 2013. doi:10.1109/TPEL.2012.2227500
- [12] C. S. Antúnez, J. F. Franco, M. J. Rider, R. Romero, "A New Methodology for the Optimal Charging Coordination of Electric Vehicles Considering Vehicle-to-Grid Technology," IEEE Trans. Sustain. Energy. vol. 7, no. 2, pp. 596-607, 2016. doi:10.1109/TSTE.2015.2505502
- [13] K. Clement-nyns, E. Haesen, and J. Driesen, "The impact of vehicle-to-grid on the distribution grid," Electr. Power Syst. Res., vol. 81, no. 1, pp. 185-192, 2011. doi:10.1016/j.epr.2010.08.007
- [14] H. Liu, Z. Hu, Y. Song, and J. Lin, "Decentralized vehicle-to-grid control for primary frequency regulation considering charging demands," IEEE Trans. Power Syst., vol. 28, no. 3, pp. 3480-3489, Aug. 2013. doi:10.1109/TPWRS.2013.2252029
- [15] C. D. White and K. M. Zhang, "Using vehicle-to-grid technology for frequency regulation and peak-load reduction," J. Power Sources, vol. 196, no. 8, pp. 3972-3980, 2011. doi:10.1016/j.jpowsour.2010.11.010
- [16] Z. Wang and S. Wang, "Grid Power Peak Shaving and Valley Filling Using Vehicle-to-Grid Systems," IEEE Trans. Power Del., vol. 28, no. 3, pp. 1822-1829, 2013. doi:10.1109/TPWRD.2013.2264497
- [17] M. Brenna, F. Foiadelli, and M. Longo, "The Exploitation of Vehicle-to-Grid Function for Power Quality Improvement in a Smart Grid," IEEE Intell. Transp. Syst. vol. 15, no. 5, pp. 2169-2177, 2014. doi:10.1109/TITS.2014.2312206
- [18] H. Liu, Z. Hu, Y. Song, J. Wang, and X. Xie, "Vehicle-to-Grid Control for Supplementary Frequency Regulation Considering Charging Demands," IEEE Trans. Power Syst., vol. 30, no. 6, pp. 3110-3119, 2015. doi:10.1109/TPWRS.2014.2382979
- [19] M. Kesler, M. C. Kisacikoglu, and L. M. Tolbert, "Vehicle-to-Grid Reactive Power Operation Using Plug-In Electric Vehicle Bidirectional Offboard Charger," IEEE Ind. Electron., vol. 61, no. 12, pp. 6778-6784, 2014. doi:10.1109/TIE.2014.2314065
- [20] J. Lin, S. Member, K. Leung, V. O. K. Li, and A. In, "Optimal Scheduling With Vehicle-to-Grid Regulation Service," IEEE Internet Things J., vol. 1, no. 6, pp. 556-569, 2014. doi:10.1109/IIOT.2014.2361911
- [21] X. Wu, L. Li, J. Zou, and G. Zhang, "EV-Based Voltage Regulation in Line Distribution Grid," IEEE Instr. and Meas. Tech. Conf. Taipei 2016. doi:10.1109/I2MTC.2016.7520568
- [22] A. Andreotti, G. Carpinelli, F. Mottola, and D. Proto, "A review of single-objective optimization models for plug-in vehicles operation in smart grid- Part I: Theoretical aspects," in Proc. Power and Energy Society General Meeting, San Diego, USA, 22-26 July 2012, pp. 1-8. doi:10.1109/PESGM.2012.6345381.
- [23] A. Andreotti, G. Carpinelli, F. Mottola, and D. Proto "A review of single-objective optimization models for plug-in vehicles operation in smart grids part ii: Numerical applications to vehicles fleets," in Proc. Power and Energy Society General Meeting, San Diego, USA, 22-26 July 2012, pp. 1-8. doi:10.1109/PESGM.2012.6345390.
- [24] X. Bai, W. Qiao, "Robust optimization for bidirectional dispatch coordination of large-scale V2G," IEEE Trans Smart Grid, vol. 6, no. 4, pp. 1944-1954, 2015. doi:10.1109/TSG.2015.2396065
- [25] W. Qi, Z. Xu, Z.-J. Shen, Hu Z, Song Y. "Hierarchical coordinated control of plug- in electric vehicles charging in multifamily dwellings," IEEE Trans Smart Grid, vol. 5, no. 3, pp. 1465-1474, 2014. doi:10.1109/TSG.2014.2308217
- [26] C. Jin, J. Tang, and P. Ghosh, "Optimizing Electric Vehicle Charging: A Customer's Perspective," IEEE Trans. Veh. Technol., vol. 62, no. 7, pp. 2919-2927, 2013. doi:10.1109/TVT.2013.2251023
- [27] A. H. Hajimiragha, C. A. Canizares, M. W. Fowler, S. Moazeni, and A. Elkamel, "A robust optimization approach for planning the transition to plug-in hybrid electric vehicles," IEEE Trans. Power Syst., vol. 26, no. 4, pp. 2264-2274, 2011. doi:10.1109/TPWRS.2011.2108322
- [28] K. Zhang, L. Xu, M. Ouyang, H. Wang, L. Lu, J. Li, "Optimal decentralized valley-filling charging strategy for electric vehicles," Energy Convers Manag., vol. 78, no. 57, pp. 537-550, 2009. doi:10.1016/j.enconman.2013.11.011
- [29] X. Wang, Q. Liang, "Energy management strategy for plug-in hybrid electric vehicles via bidirectional vehicle-to-grid," IEEE Syst J, vol. 37, no. 3, pp. 1789 - 1798, 2017. doi:10.1109/JSYST.2015.2391284
- [30] M. Shafie-khah, M. P. Moghaddam, M.K. Sheikh-El-Eslami, M. Rahmani- Andebili, "Modeling of interactions between market regulations and behavior of plug-in electric vehicle aggregators in a virtual power market environment," Energy, vol. 40, no. 1, pp. 139-150, 2012. doi:10.1016/j.energy.2012.02.019
- [31] Z. Yang, K. Li, A. Foley, C. Zhang, "Optimal Scheduling Methods to Integrate Plug-in Electric Vehicles with the Power System: A Review," in Proc. 19th IFAC World Congress, Cape Town, South Africa, 24-29 August 2014. doi:10.3182/20140824-6-ZA-1003.01804
- [32] Z. Yang, K. Li, A. Foley, "Computational scheduling methods for integrating plug-in electric vehicles with power systems: A review," Renewable and Sustainable Energy Reviews, vol. 51, no. 28, pp. 396-416, 2015. doi:10.1016/j.rser.2015.06.007
- [33] Y. Sugii, K. Tsujino, T. Nagano, "A Genetic-Algorithm based scheduling method of charging of electric vehicles," in Proc. IEEE Systems, Man, and Cybernetics, Conference Proceedings, Tokyo, Japan, 12-15 Oct. 1999, pp. 1-8. doi:10.1109/ICSMC.1999.812443
- [34] G. Celli, E. Ghiani, F. Pilo, G. Pisano, G. G. Soma, "Particle Swarm Optimization for Minimizing the Burden of Electric Vehicles in Active Distribution Networks," in Proc. Power and Energy Society General Meeting, in Proc. Power and Energy Society General Meeting, San Diego, USA, 22-26 July 2012, pp. 1-7. doi:10.1109/PESGM.2012.6345458
- [35] S. Xu, D. Feng, Z. Yan, L. Zhang, N. Li, L. Jing, J. Wang, "Ant-Based Swarm Algorithm for Charging Coordination of Electric Vehicles," Int. J. Dist. Sensor Network, vol. 9, no. 5, pp. 1-13, 2013. doi:10.1155/2013/268942
- [36] I. Rahman, P. Vasant, B. S. M. Singh, M. Abdullah-Al-WadudHybrid, "Swarm Intelligence-Based Optimization for Charging Plug-in Hybrid Electric Vehicle," In: Nguyen N., Trawiński B., Kosala R. (eds) Intelligent Information and Database Systems. ACIIDS 2015. Lecture Notes in Computer Science, vol 9012. Springer, Cham doi:10.1007/978-3-319-15705-4_3
- [37] M. Alonso, H. Amaris, J. G. Germain, J. M. Galan, "Optimal Charging Scheduling of Electric Vehicles in Smart Grids by Heuristic Algorithms," Energies, vol. 7, no. 4, pp. 2449-2475, 2014. doi:10.3390/en7042449
- [38] C. Jin, J. Tang, P. Ghosh, "Optimizing electric vehicle charging with energy storage in the electricity market," IEEE Trans Smart Grid, vol. 4, no. 1, pp. 311-320, 2013. doi: 10.1109/TSG.2012.2218834
- [39] S. Shao, M. Pipattanasomporn, and S. Rahman, "Challenges of PHEV penetration to the residential distribution network," in Proc. IEEE Power Energy Soc. Gen. Meeting, 2009, Calgary, Canada, 26-30 July 2009, pp. 1-8. doi:10.1109/PES.2009.5275806
- [40] C. D. White and K. M. Zhang, "Using vehicle-to-grid technology for frequency regulation and peak-load reduction," J. Power Sources, vol. 196, no. 8, pp. 3972-3980, 2011. doi:10.1016/j.jpowsour.2010.11.010
- [41] P. Richardson, D. Flynn, A. Keane, "Optimal Charging of Electric Vehicles in Low-Voltage Distribution Systems," IEEE Trans. Power Syst., vol. 27, no. 1, pp. 268 - 279, 2012. doi:10.1109/TPWRS.2011.2158247
- [42] S. Deilami, A. S. Masoum, P. S. Moses, M. A. S. Masoum, "Real-Time Coordination of Plug-In Electric Vehicle Charging in Smart Grids to Minimize Power Losses and Improve Voltage Profile," IEEE Trans. Smart Grid, vol. 2, no. 3, pp. 456 - 467, 2011. doi:10.1109/TSG.2011.2159816
- [43] N. Bañol A., J. F. Franco, M. Lavorato, M. J. Rider, R. Romero, "Plug-In Electric Vehicle Charging Coordination in Electrical Distribution Systems Using a Tabu Search Algorithm," IEEE 15th Int. Conf. Environment and Electrical Engineering (EEEIC), Rome, Italy, 10-13 June 2015, pp. 1-6. doi:10.1109/EEEIC.2015.7165395
- [44] O. Sundström, C. Binding, "Flexible Charging Optimization for Electric Vehicles Considering Distribution Grid Constraints," IEEE Trans. Smart Grid, vol. 3, no. 1, pp. 26 - 37, 2011. doi:10.1109/TSG.2011.2168431
- [45] A. Dogan, T. Yalcinoz, M. Alci, "A Comparison of Heuristic Methods for Optimum Power Flow Considering Valve Point Effect", Elektronika Ir Elektrotechnika, vol. 22, no.5, pp.32-37, 2016. doi:10.5755/j01.eie.22.5.16340
- [46] P. Richardson, D. Flynn, and A. Keane, "Optimal charging of electric vehicles in low-voltage distribution systems," IEEE Trans. Power Syst., vol. 27, no. 1, pp. 268-279, 2012. doi:10.1109/TPWRS.2011.2158247
- [47] C. Wu and H. Mohsenian-rad, "Vehicle-to-Aggregator Interaction Game," IEEE Trans. Smart Grid, vol. 3, no. 1, pp. 434-442, 2012. doi:10.1109/TSG.2011.2166414
- [48] H. Liang, B. J. Choi, and W. Zhuang, "Optimizing the Energy Delivery via V2G Systems Based on Stochastic Inventory Theory," IEEE Trans. Smart Grid., vol. 4, no. 4, pp. 2230-2243, 2013. doi:10.1109/TSG.2013.2272894

- [49] R.-E. Precup, S. Preitl, "Optimisation criteria in development of fuzzy controllers with dynamics," *Engineering Applications of Artificial Intelligence*, vol. 17, no. 6, pp. 661-674, 2004. doi:10.1016/j.engappai.2004.08.004
- [50] T. S. Li, C. T. Su, T. L. Chiang, "Applying robust multi-response quality engineering for parameter selection using a novel neural-genetic algorithm," *Computers in Industry*, vol. 50, no. 1, pp. 113-122, 2003. doi: 10.1016/S0166-3615(02)00140-9.
- [51] S. Vrkalic, T.-A. Teban, I.-D. Borlea, "Stable Takagi-Sugeno fuzzy control designed by optimization," *International Journal of Artificial Intelligence*, vol. 15, no. 2, pp. 17-29, 2017. doi:
- [52] R. D. Baruah, P. Angelov, "DEC: Dynamically Evolving Clustering and its application to structure identification of evolving fuzzy models," *IEEE Trans. Cybern.*, vol. 44, no. 9, pp. 1619-1631, 2014. doi:10.1109/TCYB.2013.2291234
- [53] D. E. Goldberg, *Genetic Algorithms in Search, Optimization, and Machine Learning*. Reading: Addison-Wesley Publishing Company, p.62, 1989
- [54] K. V. Price, "Differential evolution: a fast and simple numerical optimizer," in *Proc. Fuzzy Inf. Process. Soc. Conf. North Am.*, Berkeley, CA, USA, 19-22 June 1996 pp. 524-527. doi:10.1109/NAFIPS.1996.534790
- [55] J. Kennedy, R. Eberhart, "Particle swarm optimization", in *Proc. IEEE Int. Conf Neural Networks*, Perth, Australia, 27 Nov.-1 Dec. 1995, pp. 1942-1948. doi:10.1109/ICNN.1995.488968
- [56] D. Karaboga, "An idea based on honey bee swarm for numerical optimization". Technical Report TR06, Erciyes University, Eng. Faculty, Computer Engineering Department, Oct. 2005. [Online]. Available: http://mf.erciyes.edu.tr/abc/pub/tr06_2005.pdf
- [57] R. Ranjan, D. Das, "Simple and efficient computer algorithm to solve radial distribution networks," *Electr Power Compon Syst.*, vol. 31 pp.95-107, 2003 doi:10.1080/15325000390112099
- [58] GridLAB-D, [Online]. Available: <http://www.gridlabd.org/>
- [59] D.P. Chassin, K. Schneider, C. Gerkensmeyer, "GridLABD: An open-source power systems modeling and simulation environment," in *Proc. Transmission and Distribution Conference and Exposition*, Chicago, USA, 21-24 April 2008, pp.1-5. doi:10.1109/TDC.2008.4517260
- [60] MATLAB, [Online]. Available: <https://www.mathworks.com/products/matlab.html>
- [61] J. C. Fuller, B. Vyakaranam, N. Prakash Kumar, S. M. Leistriz, G. B. Parker, "Modeling of GE Appliances in GridLAB-D: Peak Demand Reduction," Technical Report-PNNL-21358 [Online]. Available: https://www.pnnl.gov/main/publications/external/technical_reports/pnnl-21358.pdf
- [62] Z. T. Taylor, K. . Gowri, S. Katipamula, "GridLAB-D Technical Support Document: Residential End-Use Module Version 1.0," Technical Report-PNNL- 17694 [Online]. Available: https://www.pnnl.gov/main/publications/external/technical_reports/PNNL-17694.pdf
- [63] R. G. Pratt, C. C. Conner, E. E. Richman, K. G. Ritland, W. F. Sandusky, and M. E. Taylor, "Description of Electric Energy Use in Single Family Residences in the Pacific Northwest," DOE/BP 13795 21, Bonneville Power Administration, Portland, OR, 1989. [Online]. Available: <https://elcap.nwcouncil.org/Documents/Electric%20Energy%20Use%20Single%20Family.pdf>
- [64] EN 50160, voltage characteristics of electricity supplied by public distribution systems, 1999.
- [65] S. Shao, M. Pipattanasomporn, and S. Rahman, "Grid Integration of Electric Vehicles and Demand Response With Customer Choice," *IEEE Trans. Smart Grid.*, vol. 3, no. 1, pp. 543-550, 2012. doi:10.1109/TSG.2011.2164949
- [66] FHA, "Summary of Travel Trends: 2009 National Household Travel Survey," p. 82, 2011.
- [67] J. D. Dogger, B. Roossien, and F. D. J. Nieuwenhout, "Characterization of Li-ion batteries for intelligent management of distributed grid connected storage," *IEEE Trans. Energy Convers.*, vol. 26, no. 1, pp. 256- 263, 2011. doi:10.1109/TEC.2009.2032579 E.
- [68] E. Bompard, E. Carpaneto, G. Chicco, and R. Napoli, "Convergence of the backward / forward sweep method for the load-flow analysis of radial distribution systems," *Int. J. of Elect. Power & Energy Syst.*, vol. 22, pp. 521-530, 2000. doi:10.1016/S0142-0615(00)00009-0.
- [69] R.-E. Precup, R.-C. David, E. M. Petriu, M.-B. Rădac, S. Preitl, J. Fodor, "Evolutionary optimization-based tuning of low-cost fuzzy controllers for servo systems," *Knowledge-Based Systems*, vol. 38, no. 9, pp. 74-84, 2013. doi:10.1016/j.knsys.2011.07.006
- [70] D. Zaharie, "Influence of crossover on the behavior of Differential Evolution Algorithms," *Applied Soft Computing*, vol. 9, no. 3, pp. 1126-1138, 2009. doi: 10.1016/j.asoc.2009.02.012
- [71] A. W. Mohamed, H. Z. Sabry, M. Khorshid, "An alternative differential evolution algorithm for global optimization," *Journal of Advanced Research*, vol. 3, no. 2, pp. 149-165, 2012. doi:10.1016/j.jare.2011.06.004
- [72] D. Karaboga B. Basturk, "On the performance of artificial bee colony (ABC) algorithm," *Applied Soft Computing*, vol. 8, no. 1, pp. 687-697, 2008. doi: 10.1016/j.asoc.2007.05.007

APPENDIX A

TABLE A. NUMBER OF HOUSES AND EV IN EACH BUS

Bus No	House Num.	Number of EV		
		EV1	EV2	EV3
1	0	0	0	0
2	27	0	0	0
3	24	7	3	3
4	32	6	2	6
5	16	0	6	0
6	16	7	0	0
7	54	0	0	0
8	54	0	0	0
9	16	4	4	6
10	16	7	1	5
11	12	2	2	7
12	16	9	5	0
13	16	7	3	3
14	32	21	0	0
15	16	7	3	3
16	16	1	6	7
17	16	7	0	0
18	24	0	7	7
19	24	0	0	14
20	24	0	21	0
21	24	1	2	10
22	24	10	7	3
23	24	6	4	11
24	113	14	9	5
25	113	26	6	3
26	16	7	0	0
27	16	3	5	6
28	16	0	0	0
29	32	3	2	5
30	55	10	6	6
31	41	0	0	0
32	58	0	0	21
33	17	0	0	0