Heuristic Optimization of EV Charging Schedule Considering Battery Degradation Cost

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***Abstract*—It is expected that electric vehicles (EVs) will be important part of smart gird, not only in form of load but also as distributed energy source in Vehicle to Grid (V2G) system. As increase of EVs integration, V2G contributes to improve flexibility, reliability and stability of grid by providing ancillary services. These services, however, could accelerate degradation of battery whose price is almost half of EV. Thus, battery degradation cost must be considered while scheduling of EV charging. In this paper, a battery degradation cost model of EV lithium-ion batteries was incorporated in the optimal charging schedule of 400 EVs. EVs are located to 33 bus system in order to consider network losses in calculations. Heuristic algorithms such as Genetic Algorithm (GA), Differential Evolution (DE), Particle Swarm Optimization (PSO) and Artificial Bee Colony (ABC) are used for solving the associated optimization problem. The objective function aims to maximize user profit under dynamic pricing. Also, distribution system and EVs constraints are considered during optimization. The numerical results illustrate that each of the used heuristic algorithms able to mitigate peak loads and improve voltage levels. GA presents the most profitable charging scheduling in terms of EV owners.**

***Index Terms*—Electric vehicles; Optimization; Heuristic algorithms; EV Charging Schedule; Vehicle to Grid.**

I. INTRODUCTION

Number of EV has been rapidly increasing in transportation due to environmental and economic reasons. This means, charging load of EVs will constitute the substantial portion of demanded power from grid in near future. Moreover, many of EVs arrival home and plugged in time corresponds peak hours of residential distribution system. In case of charging process of EV is not scheduled, it may create defects in distribution system such as voltage limit violation, overload, increase in peak etc. On the other hand, EV batteries have ability to inject energy to grid if required connections are provided. The concept which allows bidirectional energy flow between EVs and grid is referred as Vehicle to Grid (V2G) [1]. The researches reveal benefits of V2G for distribution system operation such frequency regulation, voltage support, peak load shaving and maintaining the power system reliability [2].

In [3], charge/discharge coordination is carried out to provide voltage regulation on grid. In [4], maximum incomes from parking areas are aimed while the voltage is supported by deciding charging mode of EVs. In [5], [6], frequency regulation service is provided taking into account of state of charge rates of EVs. In [7], the authors aim to maximize the long term charging fairness while flattening the peak load. While EVs are used for auxiliary service operations, battery degradation is not considered for cost calculations in cited paper above. However, battery degradation is one of most important factor in cost calculation due to batteries represent the major part of EV cost [8]. In [9], all factor which affect life of lithium-ion batteries are investigated and general cycle life and degradation model of a battery is created associated with V2G applications. In [10], degradation model of battery is modelled and degradation rates of batteries are compared for different conditions. In [11], battery degradation cost of an EV is optimized for charge/discharge process considering electricity price. In [12], the energy cost charging process and degradation of the battery are taken into account as operating cost. However, the cost is calculated on generalized values, and thus factors which affect battery degradation level is ignored. In [13], loss of battery capacity was calculated as a function of driving days. Cited researches which take into account battery degradation are calculated for single EV and the results are generalized. Also, battery degradation cost in V2G application is not carried out associated with a distribution system. Hence, distribution system constraints and system losses are ignored.

This paper contributes to combine battery degradation cost model with charge schedule of EVs which have ability of bidirectional load flow. Moreover, 400 EVs are integrated to 33 bus test system in order to consider system losses unlike previous work. Objective function of optimum scheduling of EV charging problem aims to maximize user profit under real time pricing. This approach does not solve only charge scheduling problem, but also maximizes overall user profit while satisfying distribution system and EV constraints. The methodology considers the uniform distribution of EVs' arrival and departures time and initial state of charge (SOC) as well as different battery sizes and battery degradation is calculated separately for each EV. Associated optimization problem is solved using heuristic algorithms (GA, PSO, DE and ABC) due to ability of their features to solve large scale problems effectively. Numerical results of simulated heuristic algorithms are compared in

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terms of user profit and distribution system improvement.

II. BATTERY DEGRADATION COST MODEL

Battery is the most important part of EV and it costs the nearly half of EV price. Besides, lithium-ion batteries are the most common battery technology for EVs in development. Advantages of lithium-ion batteries are no memory effect and high energy density. Cycle life of a battery represents the number of the charge-discharge cycle before reaching 80 % of its rated capacity and it is considered to estimate the battery life in V2G applications. Factors which have potential to affect life of a lithium-ion battery are number of cycle, charge discharge rates, total operational temperature, and depth of discharge (DoD). However, charge-discharge rate and operational temperatures can be neglected due to current rates are quite limited in V2G application [10], [14]. Battery degradation is highly depending on quantity of DoD. DoD indicates that discharge action from 100 % (100-D) and charging back to 100 % SOC [9, 15]. The number of cycles of the battery varies inversely with D and best fit equation as follows

$$Ln(L) = -0.795 Ln(D) + 6.5425, \tag{1}$$

where L indicates number of battery cycle life. Equation (1) can be transformed to

$$L = 694 \times D^{-0.795}. \tag{2}$$

Battery cost fell to less than 227 $ per kWh by the end of the 2016 [16]. Hence, Unit Battery Degradation Cost $(UBDC)$ is calculated per KWh as follows [11]

$$UBDC = 227 \times \frac{1}{L}, [\$ / kWh]. \tag{3}$$

III. FORMULATION OF EV CHARGING SCHEDULE

The presented methodology solves the optimal scheduling of EV charging problem for the energy transfer between EV and the grid considering their constraints.

Figure 1 shows the model which is solved for each time. N is the number of EVs and each EV is indexed by $n = 1, 2, ...N$. t_n^{arr} and t_n^{dep} indicates the times which EV arrives home from work and EV departures for work, respectively. Black boxes denote times which EV is plugged in and considered for optimization process. Δt defines the time interval between t and $t+1$. The model is solved in every time interval. The charging schedule of each EV is generated between its arrival and departure time. Operational constraints such as voltage limits, active power generation limits must be satisfied by the model as the charging schedule is being optimized. Also, each EV must be fully charged at departure. Fully charged means charged at maximum allowed state of charge level.

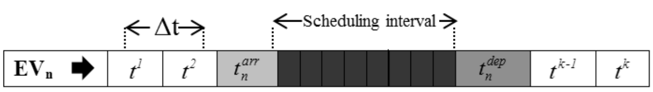

Fig. 1. Solution cycle of each EV.

Objective Function: Total cost for users includes charging and battery degradation costs while users receive incentive payments as provision of discharged energy in V2G. The objective function of optimum scheduling of charging is presented by (4) and aims to maximize user profit under real time pricing [9]

$$\min \left\{ \sum_{t=1}^{t^k} \left[\begin{array}{c} -\left(\sum_{n=1}^{N} CC_n(\Delta t) \right) - \\ \left(\sum_{n=1}^{N} BDC_n^{tot}(\Delta t) \right) + \left(\sum_{n=1}^{N} I_n(\Delta t) \right) \end{array} \right] \right\}. \tag{4}$$

$CC_n(\Delta t)$ indicates the charging cost and calculated as given in (5)

$$CC_n(\Delta t) = E_n^{ch}(\Delta t) \times \alpha(\Delta t), \tag{5}$$

where E_n^{ch} is charged energy and α is rate of incentive during Δt.

$BDC_n^{tot}(\Delta t)$ comprises degradation cost during V2G $\left(BDC_n^{V2G}(\Delta t)\right)$ and increased cost of motion $\left(BDC_n^{motion}(\Delta t)\right)$. Battery degradation cost during V2G is calculated multiplying discharged energy $\left(E_n^{dis}\right)$ and $UBDC_n^{V2G}$. Since $UBDC$ is increased after V2G, cost of motion is increased and added to battery degradation cost as follows

$$BDC_n^{tot}(\Delta t) = E_n^{dis}(\Delta t) \times UBDC_n^{V2G} + BDC_n^{motion}(\Delta t). \tag{6}$$

$I_n(\Delta t)$ is the amount of incentive payments for discharged power. Total amount of incentive payment is calculated as follows

$$I_n(\Delta t) = E_n^{dis}(\Delta t) \times \lambda(\Delta t), \tag{7}$$

where E_n^{dis} is discharged energy and λ is rate of incentive during Δt.

Constraints: Total distribution system load $\left(P_{DN}(t)\right)$ includes total household load, total EV load and losses on the network. $P_{DN}(t)$ and voltage of each bus $V_m(t)$ must be between maximum and minimum limit. Besides, EV cannot be discharged lower than allowed minimum state of charge $\left(SOC_n^{min}\right)$ and EV cannot be charged higher than allowed maximum state of charge $\left(SOC_n^{max}\right)$. Also, battery of each EV must be fully charged at departure time.

IV. OPTIMIZATION OF EV CHARGING SCHEDULE USING HEURISTIC ALGORITHMS

Input variables include system data and EV data. System data indicates that load data on the buses and electrical data between lines. EV data consists of departure time, arrival time, max./min. SOC, battery capacity, current SOC, charge/discharge power and charge efficiency of each EV. Min./max. SOC are already introduced to charge controller by EV owner. Arrival and departure time are provided by owner or it is estimated based on historic data. When EV plugged in, current SOC of EV is detected. Charge/discharge statues of EV are decided by system operator according to these input variables. Status of each EV is considered as control variables at each t as follows

$$u(t)=\{u_n(t)\,|\,n=1,2..N\}, \tag{8}$$

where $u_n(t)$ indicates the control action on EV. $u_n(t)$ = 1 means EV n is charging. $u_n(t)$ = -1 means EV n is discharging and $u_n(t)$ = 0 means EV n neither charges nor discharges. The charging status of each EV is decided by heuristic algorithms for each t. Heuristic algorithms have ability to scan wide range of solution quickly and they are effectively used in solution of power systems problem [17]. Best solution is selected considering their fitness values as follows

$$p_i=\frac{fitness_i}{\sum_{i=1}^{mi} fitness_i}, \tag{9}$$

where mi is the total number of potential solution. i is the number of potential solution, $i=1..mi$. Each potential solution include Dm dimensional control variable vector of u. The solution is improved during iterations using characteristics operators of each algorithm. Operators of each algorithm are explained below.

A. *Genetic Algorithm*

Genetic algorithm is a global search method which simulates the biological evolution. The three operators of Genetic Algorithm are selection, crossover and mutation [18]. Population of GA represents the solution set of a problem. Solution set consist of chromosomes whose best fitness are selected and transfer to next population. Reproduction mechanism determines the probability of chromosome to be reproduced. Systematic gene exchange between chromosomes is refers crossover mechanism. Mutation is random gene exchange which increases the diversity of population. Different mutation methods are available according to the coding types of individuals.

B. *Differential Evolution*

New individuals are produced with mutation, cross over and selection operators [19]. In mutation, donor vector $(v_{i,j}(t))$ is produced by adding third chromosome to multiplication of scaling factor (F) and differences of two chromosomes as follows

$$v_{i,j}(t+1)=x_{r1,j}(t)+F\left(x_{r2,j}(t)-x_{r3,j}(t)\right). \tag{10}$$

In cross over, current vector $X_i(t)$ and donor vector $V_i(t)$ are mixed with Crossover Rate (CR) and trial vector $U_i(t)$ is produced as follows

$$u_{i,j}(t)=\begin{cases} v_{i,j}(t), & if \quad rand\ [0,1]\le CR \ \ j=j_{rand}, \\ x_{i,j}(t), & otherwise. \end{cases} \tag{11}$$

In selection, the most fitted chromosome is sent to the next generation as follows

$$X_i(t+1)=\begin{cases} U_i(t), & if \ \ f(U_i(t))\le f(X_i(t)), \\ X_i(t), & otherwise. \end{cases} \tag{12}$$

C. *Particle Swarm Optimization*

PSO algorithm simulates the bird swarm foraging positions. Each particle represents a bird and its behavior. Velocity and the position of the particle are operators of PSO [20]. Velocity of the i th particle is updated as follows

$$v_t^{(t+1)}=wv_i^{(t+1)}+c_1r_1\left(pbest_i-x_i^{(t)}\right)+ \\ +c_1r_1\left(gbest-x_i^{(t)}\right), \tag{13}$$

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

$$x_i^{t+1}=x_i^t+v_i^{t+1}. \tag{14}$$

D. *Artificial Bee Colony*

ABC is the algorithm based on food searching of bees. A bee colony consists of three group bees; employed, onlookers and scouts [21]. Employer bee determine food source considering neighborhood in their memory. Employed bees share food source data with onlooker bees. Onlooker bees decide a food source based on fitness degree of them. An employed bee which leaves a food source becomes a scout and start to search to search new sources randomly. Neighborhood principle is considered by bees in order to find the new food sources. Neighbors of quality food sources are selected as new sources as follows

$$v_{i,j}=x_{i,j}+\phi_{i,j}\left(x_{i,j}-x_{k,j}\right), \tag{15}$$

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

V. SIMULATION RESULTS

It is assumed that EVs are using for commuting propose so they leave to work in the morning and back in the evening. EV group consists of three types of models of EVs currently on the market: 128 Mitsubishi i-MiEV with 16 kWh battery pack [22], 134 Nissan Leaf with with 30 kWh battery pack [23], 138 Chevrolet Bolt with 60 kWh battery pack [24]. EVs charging powers are 3.3 kW, 3.3 kW and 7.6 kW respectively. Distributions of parameters of EVs are given in Table I.

TABLE I. DISTRIBUTIONS OF PARAMETERS FOR ALL EVS.

Parameters	Distribution
SOC_n^{arr}	U [0.3, 0.7]
SOC_n^{min}	U [0.3, 0.4]
SOC_n^{max}	U [0.90, 0.99]
$\eta_{ch/dis}$	U [0.85, 0.95]
t_n^{arr}	[μ,σ] [7.30, 1]
t_n^{dep}	[μ,σ] [17.30, 1]

The plug in and plug out times of EVs are generated based on uniform distribution with the mean at 7.30 and 17.30 with 1 h standard deviation [25]. Charging/discharging efficiency is uniformly distributed between 0.85 and 0.95.

33 bus residential distribution system is considered for implementation of optimum charging schedule with nominal voltage of 12.66 kV and base power of 100 MVA. 1000 houses are located on each bus proportional with test load data of the network [26] and 400 EV are randomly located on buses. Load profile of the distribution system created using GridLAB-D which allows to simulate each house appliances power consumption taking into account user patterns [27], [28]. Voltage variation limit is specified 10 % [29] and maximum load capacity is defined as 5000 kW. Load flow is performed using B/F sweep method [26].

The simulation scenario is optimal scheduling to decide charging/discharging status of 400 EVs from 00:00 midnight to 6:00 on the next morning. This 18 h period of time is divided equally into 215 slots of length Δt = 10 min. Price signal is shown in Fig. 2 [30]. Users are awarded 0.40 \$/kWh if EVs supply energy to grid between 17.00–19.00.

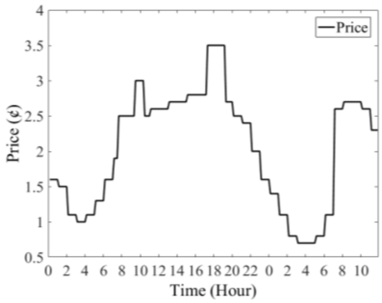

Fig. 2. Real time pricing tariff.

In Fig. 3, total load of distribution system w/ and w/o EVs are illustrated with distribution of EVs arrival and departure. EVs arrive home between 15.00–20.40 and departure from home between 4.50–11.00. 80 % of EVs arrive home before 18.00 and start charging. Therefore, significant part of EVs charges during peak hours and charging power peak reaches to 1646 kW at 19.10. Peak load increases from 4935 kW to 6430 kW with charging load and increased losses at 18.10. Maximum load limit is highly violated in case of uncontrolled charging.

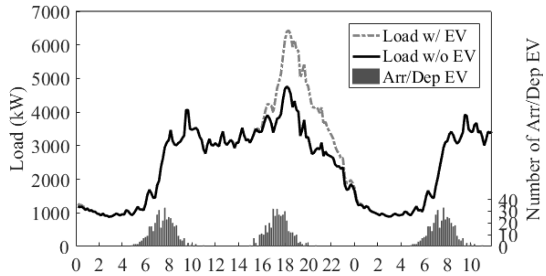

Fig. 3. Distribution system load w/ and w/o EV with arrival and departure distribution of EV.

In Fig. 4, minimum voltage values of distribution system are illustrated. Minimum voltage level of the system w/o and w/ EVs are 0.89 p.u. and 0.86 p.u., respectively. Minimum bus voltage is less than 0.9 p.u. for a short time w/o EV. However, minimum bus voltage decreases less than 0.9 p.u. between 17.00–19.45 in case of uncontrolled EV charging.

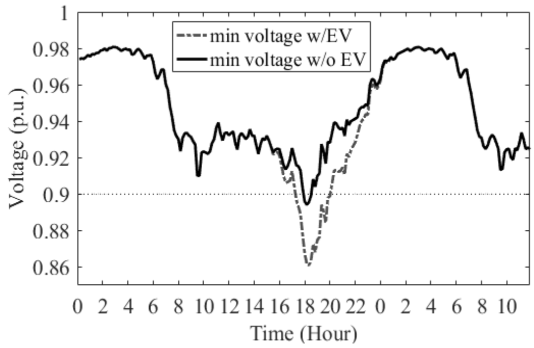

Fig. 4. Voltage magnitude w/ and w/o EV.

In this paper, optimum scheduling of EV charging is provided using heuristic algorithms such as GA, PSO, DE and ABC. Population sizes and the iteration numbers of algorithms are specified as 80 and 100, respectively. The best values of operators of algorithms are chosen based on experiment as follow:

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

DE: $[(F),(CR)]$ = [0.8, 0.5], PSO: $[w, c1, c2]$ = [0.5, 1.0, 1.5], ABC: Limit= [100].

In Fig. 5, convergence curve of cost of EV charging using heuristic algorithms are presented. Negative values mean EV owners pay to distribution company while positive values indicate that distribution company has to pay to EV owner. Daily cost of EV charging is \$5.14, -\$0.23, -\$3.24 and -\$17.26 using GA, DE, PSO and ABC, respectively. Although GA initializes with lowest profit, it has the best result.

Detailed daily costs of scheduled charging are given in Table II. Charging and battery degradation cost with PSO are \$ 89.28 and \$ 402.33. These are minimum charging and battery degradation cost along given optimization algorithms. Besides, PSO has the minimum incentive rate as \$ 491.38, as well. DE has the highest incentive and battery degradation cost as $ 517.60 and $ 430.44, respectively. Each of given algorithm provides to decrease charging costs by taking advantage of the incentive. However, GA provides the maximum profit such distribution company has to pay to users with GA scheduling.

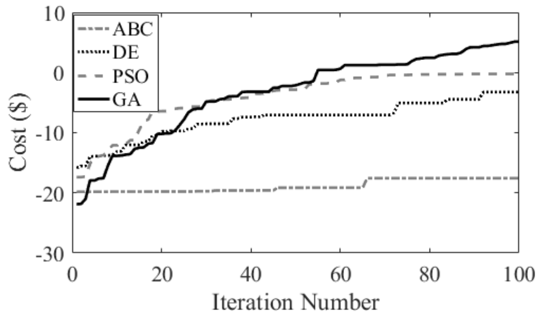

Fig. 5. Convergence curve for optimal scheduling of EV charging.

TABLE II. TOTAL INCOME AND EXPENSES OF EV OWNERS USING GA, PSO, DE, ABC.

	GA	PSO	DE	ABC
Charging Cost ($)	89.32	89.28	90.40	91.42
Bat.Degr.Cost ($)	408.69	402.33	430.44	425.11
Incentive rate ($)	503.15	491.38	517.60	498.97
Penalty	0	0	0	0
Total ($)	5.14	-0.23	-3.24	-17.56

As an example, specifications of the 48th EV are given in Table III. The EV arrives home at 17.24 with 42 % SOC and connected to bus 22. Min. and max. SOC defined by the user are 31 % and 92 %, respectively. While charge/discharge power 3.3 kW, charge efficiency 0.94 and discharge efficiency is 1, respectively. Also, departure time is defined as 06.19.

TABLE III. SPECIFICATIONS OF 48TH EV.

EV Specifications	Values
ID Number	48
Bus Number	22
Arrival/ Departure time	17.24/06.19
Min/Max/Init SOC (%)	31/92/42
Battery cap/(kWh)	30
Ch/Disch power (kW)	3.3
Ch/Disch efficiency	0.94/1

As seen in Fig. 6, EV arrives home with SOC of 42 %. Discharging power is 3.3 kW and charging power is 3.11 kW due to efficiencies. EV discharges partially until SOC decreased to 35.81 %. Then charging is stopped for a while by system operator considering system requirements and electricity price. After partially charging, EV starts non-stop charging from 1.30 to 6.10. SOC of the EV has reached to defined max. SOC (92 %) before departure time. Partially charges and discharges are seen sharp due to ten minute simulation interval. It would be square if simulation was performed with one minute interval.

In Fig. 7, total load variation of distribution system is illustrated. Peak load was 4761 kW w/o EV and it increased to 6430 kW with uncontrolled charging of EVs. However, optimization algorithms provide discharging energy during high price time while they are charging at low price times. Not only peak increase is prevented but also peak load is reduced with optimization algorithms. Peak loads are reduced to 4098 kW, 4020 kW, 4145 kW and 4100 kW using GA, DE, PSO and ABC, respectively.

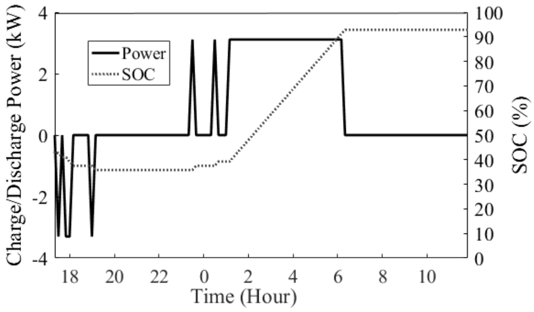

Fig. 6. Charge/discharge and SOC curve of 48th EV.

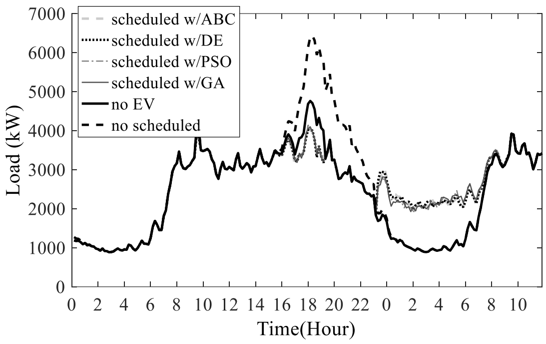

Fig. 7. Total load of distribution system.

In Fig. 8, minimum voltage level of distribution system is illustrated. Minimum bus voltage is already below the limit value at peak time and it falls to 0.86 p.u. with adaptation of EVs in the system. Optimization algorithms provide to increase minimum voltages higher than 0.90 p.u. for each time interval. Minimum bus voltages are 0.907 p.u. using GA, DE, PSO and it is 0.908 p.u. using ABC.

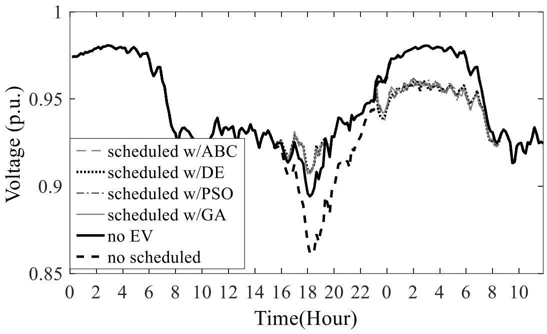

Fig. 8. Minimum voltage of distribution system.

VI. DISCUSSION

The increase in the number of EVs charging activities affect grid negatively. Meanwhile, it also offers opportunity for EVs to be used as energy sources in V2G. Nevertheless, the high cost of battery is still huge challenge since intensive and deeper use accelerates the battery degradation. Hence, relative cost of the battery must be considered to optimize scheduling of EV charging in V2G.

In simulated case, arrival times of EVs are mostly between 17.00 and 18.00. Peak load is increased by 30 % at 18.10, where peak load occurs. At this moment, total load increases to 6430 kW while minimum bus voltage decreases to 0.86 p.u. Hence, charge/discharge coordination of the

EVs is provided not to exceed system limits. After coordination, peak values are below 5000 kW and voltage values are above 0.9 p.u. using each algorithm.

Statues of EVs can be charge, discharge, neither charge nor discharge. Charge/discharge statues of EVs are decided using heuristic algorithms for each time. EV owners receive incentives as much as the amount of energy they transfer to the network while paying for charging process. The objective function aims to maximize user profit under real time pricing. Also, battery degradation is considered for calculation. EV owners receive incentive depends on discharged energy but battery degradation cost increases proportional to depth of discharge. Incentive rate of EV is the highest and battery degradation cost is also highest using DE. PSO provides minimum battery degradation cost but it is not able to provide highest incentive to EV owners. GA does not provide highest incentives or minimum battery degradation cost but GA presents most profitable charging schedule.

VII. CONCLUSIONS

This paper presents solution for maximizing user profit using heuristic algorithms accounting for battery degradation as well as costs of variable electricity costs and incentives. Battery degradation cost model was integrated in the optimal charge scheduling of EVs. Charging schedule guarantees that EVs are fully charged at departure. In addition, the charging schedules satisfied operational constraints, taking into account voltage and load boundaries. The numerical results illustrate that each simulated algorithm, GA, PSO, DE and ABC respond system requirements and EV owner expectations. The owners are payee using GA although they are payer to distribution company using PSO, DE and ABC. As a result, GA is the best performing algorithm along simulated heuristic algorithms.

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