

Performance Analysis of Optimal Online and Delayed Charging of Plug-in Electric Vehicles

Somayeh Hajforoosh, *Student Member IEEE*, Mohammad A.S. Masoum, *Senior Member, IEEE*,
Syed M. Islam, *Senior Member, IEEE*

Abstract- Electric utilities are concern about the impacts of uncoordinated plug-in electric vehicle (PEV) charging on smart grids (SGs) particularly during the peak load periods. This paper implements an online coordinated charging genetic algorithm (OL-CC-GA) for PEVs in SG that can also perform delayed (e.g., partial-overnight or full-overnight) vehicle charging by reducing the distribution transformer loading. The algorithm will minimize the total costs associated with energy generation and grid losses while also maximizing the number of PEVs that are being charged within each time interval (e.g., $\Delta t=5\text{min}$) considering distribution transformer loading and voltage regulation limits. Detailed simulations are performed for a 19-node test feeder populated with PEVS using OL-CC-GA and compared with uncoordinated and delayed charging strategies.

Index Terms- Plug-in electric vehicles, online PEV coordination, GA, and smart grid.

I. INTRODUCTION

Recent developments in smart grid (SG) along with the growing concerns about environment have increased the interests of public and electric utilities in plug-in electric vehicles (PEVs). It is well-known that uncoordinated PEV charging at high penetration levels will have detrimental impacts on the grid operation, losses and voltage profiles [1-4]. The main impact of uncoordinated PEV charging is adding new time-variant loads that can increase the strains on the generation units, transmission and distribution systems [5-8] and can result in unacceptable voltage drops and lower power quality [2].

To mitigate the negative impacts of random PEV charging on the power grid, it is critical to develop efficient charging coordination algorithms [9]. Some of the existing PEV charging algorithms are “offline” in the sense that they depend on information about the future status of the vehicles such as plug-in times and battery state of charges (SOCs) to decide the charging schedules. That is, the arrival time and charging demand of a PEV are assumed to be known or estimated prior to the arrival of the PEV. For example, Ma et al. [10] requires all PEVs to negotiate with the charging station about their charging schedules one day ahead. This coordination approach is not always practical as it depends on the accuracy and the availability of the predicted PEV information. Furthermore, in many practical applications, the PEV charging profile is revealed only after it arrives at the charging station or connects to the charging pole. In this paper, we are interested in developing an online charging algorithm that schedules PEV charging based on the information of the already plugged-in vehicles.

There have been some recent studies on online PEV charging [11-13]. Gerding et al. [12] proposes an online auction protocol that vehicle owners use agents to bid for the charging opportunities. Masoum et al. [13] studies the coordinated charging of PEVs in residential distribution systems to reduce

the power losses. He et al. [14] considers the scheduling of PEV charging and discharging in a small geographic area and proposes an online charging algorithm based on an assumption that no future PEV will arrive when a charging schedule is made. Refs [15] refer to the implementation of online PEV coordination algorithms for peak load shaving and cost minimization, respectively. Several other authors have proposed probabilistic models and charging coordination strategies considering day ahead or real time markets [16-18]. In this paper a heuristic-based online coordinated charging genetic algorithm (OL-CC-GA) is implemented for charging of PEV batteries in SG that minimizes the cost associated with energy generation, grid losses while maximizing the number of charged PEVs, regulating node voltages and reducing distribution transformer loading. OL-CC-GA also considers changing of the distribution transformer loading for online and delayed (e.g., full-overnight and partial-overnight) PEV charging. Simulations are performed for a 19-node test feeder populated with PEVS using OL-CC-GA and compared with uncoordinated and delayed charging strategies. This method is also applicable for Large-scale penetration of PEVs [21].

II. PROBLEM FORMULATION

Online coordination of PEV charging is a real time optimization problem that requires formulation of a comprehensive objective function and a high speed optimization method to quickly capture best solutions. In this paper, the nonlinear objective function of Eq. 1 is defined for the PEV coordination problem to maximize the number of vehicles that are being charged (N_{PEV-ON}) at each time slot $\Delta t = 5\text{min}$ while also minimizing the costs associated with energy generation ($F_{cost-gen}$) and grid losses ($F_{cost-loss(t)}$):

$$\max F(t) = \frac{I + N_{PEV-ON}(t)}{F_{cost-gen}(t) + F_{cost-loss}(t)} = \frac{I + N_{PEV-ON}(t)}{\sum_t K_E P_{loss}(t) + \sum_t K_{t,G} D_{total}(t)}, t = \Delta t, 2\Delta t, \dots, 24 \text{ hours} \quad (1)$$

$$\text{where } P_{loss}(t) = \sum_{k=0}^{n-1} R_{k,k+1} \left(\left| V_{k+1}(t) - V_k(t) \right| \left| y_{k,k+1} \right| \right)^2.$$

Eq. 1 is subject to the following voltage and demand (transformer loading) constraints:

$$V_{min} \leq V_k(t) \leq V_{max}, \text{ for } k = 1, \dots, n \quad (2A)$$

$$D_{total}(t) = \sum_{k=1}^n P_k(t) = \sum_{k=1}^n (P_{Load_k}(t) + P_{PEV_k}) \leq D_{max}(t) \quad (2B)$$

$$t = \Delta t, 2\Delta t, \dots$$

$$\text{where } D_{max}(t) = \text{Max} \{DL(\Delta t), DL(2\Delta t), \dots, DL(m\Delta t)\}$$

$$m = 1, \dots, 288$$

In Eqs.1, $\Delta t = 5 \text{ min}$ is the time interval; $K_E = 50 \$/MWh$ and $K_{t,G}$ are the costs per MWh of losses [13] and generation (Fig. 1), respectively; k and n are the node number and total number of nodes; $R_{k,k+1}$ and $y_{k,k+1}$ are the resistance and reactance of the line segment between nodes k and $k+1$, respectively; V_{\min} and V_{\max} are the lower and upper voltage limits, respectively; $D_{\max}(t)$ is the maximum demand level that would normally occur without any PEVs during a day. In this paper, $D_{\max}(t)$ is the maximum load (maximum distribution transformer loading) for the selected DLC and DL is the daily load at m^{th} time slot. The backward-forward sweep method is used to calculate load flows and bus voltages [19].

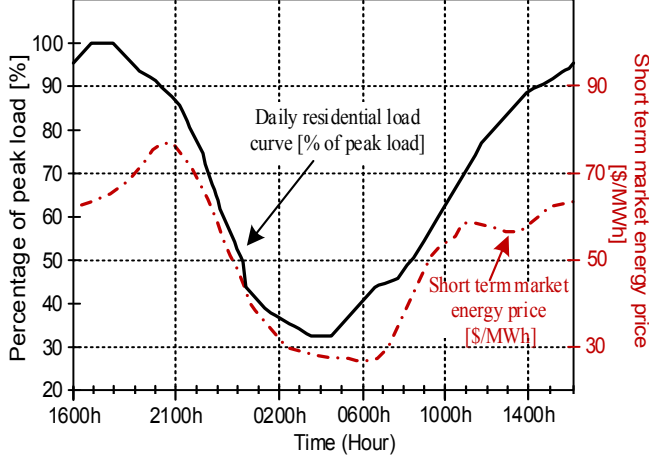


Fig. 1. Daily residential load curve (DLC) and short term market energy price (MEP) [13].

III. PROPOSED ONLINE COORDINATED CHARGING GENETIC ALGORITHM (OL-CC-GA) FOR PEVS

Genetic algorithms (GAs) are based on the principle of natural evolution that uses population genetics to capture high quality near optimal solutions [20, 22-23]. The variables are encoded into a binary string as a set of genes corresponding to chromosomes in biological systems. They use a set of points (chromosomes) as the initial conditions. A group of chromosomes are called a population. Each chromosome is a string of binary codes (genes) and may contain substrings. The quality of a string is evaluated using a fitness function which is usually derived from the objective function. During each generation (iterative procedure), a new set of strings with improved performance is generated using the reproduction, crossover and mutation GA operators.

A. Initial Population and Structure of Chromosomes

In this paper, each chromosome contains the status of all PEVs where digit “1” corresponds to a PEV being charged while digit “0” indicates the charging has not been started or already finished. Fig. 2 shows the proposed structure of the GA chromosome.

B. GA Fitness Function

The inverse algebraic product (Eq. 3) of the proposed penalty functions for voltage (Eqs. 4) and demand (Eq. 6) is used as the fitness function to combine the PEV coordination objective function (Eq. 1) and constraints (Eqs.2):

$$F_{\text{fitness}}(t) = F_F(t) / (F_V(t) \times F_D(t)) \quad (3)$$

$$F_V(t) = \prod_{k=1}^n F_{V,k}(t) \quad (4)$$

$$F_{V,k}(t) = \begin{cases} e^{\alpha_{V1}(1-V_k(t))}, & V_k(t) \leq V_{\min} \\ 1, & V_{\min} \leq V_k(t) \leq V_{\max} \\ e^{\alpha_{V2}(V_{\max}-V_k(t))}, & V_k(t) \geq V_{\max} \end{cases} \quad (5)$$

$$F_D(t) = \begin{cases} 1, & D_{\text{total}}(t) \leq 1 \\ e^{\alpha_D(D_{\text{total}}(t)-1)}, & D_{\text{total}}(t) \geq 1 \end{cases} \quad (6)$$

where $F_F(t)$, $F_V(t)$ and $F_D(t)$ are the objective function, bus voltage penalty function and demand (distribution transformer loading) penalty function at time t , respectively; α_{V1} , α_{V2} and α_D are the coefficients used to adjust the slopes of the penalty functions. The voltage and demand penalty functions are shown in Figs. 3(a) and 3(b), respectively.

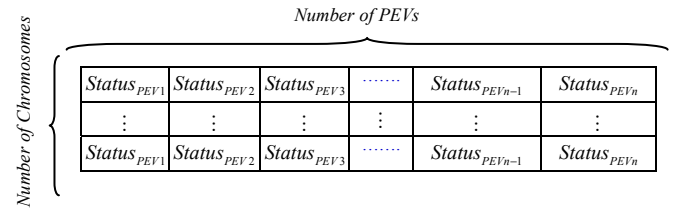


Fig. 2. The proposed GA structure of chromosome.

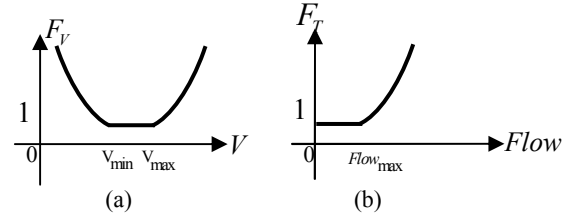


Fig 3. Penalty functions to compute fitness (a) F_V , (b) F_T .

C. Binary Genetic Algorithm Operators

Genetic operators usually consist of reproduction, crossover and mutation operators. They are stochastic transition rules applied to each chromosome during each generation procedure to generate a new improved population from an old one. Reproduction selects two parent strings from the population of strings on the basis of “roulette-wheel” mechanism, using their fitness values. This is to ensure that the expected number of times a string is selected is proportional to its fitness relative to the rest of the population. Therefore, strings with higher fitness values have a higher probability of contributing offspring.

Crossover selects a random position (crossover point) in the string and swapping the characters either left or right of this point with another similarly partitioned string. In this paper the characters to the right of a crossover point are swapped. Mutation randomly modifies a string position by changing “0” to “1” or vice versa, with a small probability. This will prevent complete loss of genetic material through reproduction and crossover by ensuring that the probability of searching any region in the problem space is never zero.

D. Proposed GA at Each Time Slot (Δt)

The proposed online coordinated charging genetic algorithm (OL-CC-GA) for PEVs in SG consists of eight steps:

Step 1: Input power system parameters, and optimization data. Read smart meters to check PEV entrances time and location for new connected PEVs.

Step 2: Assume N_{Ch_max} and N_{it_max} . Set initial counters and parameter values (e.g., $N_{Ch} = N_{it} = 1$). Use a random generator to initialize the position and velocity vectors.

Step 3 (Fitness Process):

Step 3A: Run power flow for each set of chromosome and compute the objective function (Eq.1).

Step 3B: Compute the proposed penalty functions (Eq.3).

Step 3C: If $N_{ch} \leq N_{ch_max}$ go to step 3A.

Step 4 (Reproduction Process):

Step 4A: Define total fitness as the product of all fitness values for all chromosomes.

Step 4B: Run a tournament for selection process. Select a new combination of chromosomes.

Step 5 (Crossover Process):

Step 5A: Select a random number (R_1) for mating two parent chromosomes.

Step 5B:

If R_1 is less than the values of crossover, then combine the two parents, generate two offspring and go to Step 5D.

Step 5C: Else, transfer the chromosome with no crossover.

Step 5D: repeat steps 5A to 5D for all chromosomes.

Step 6 (Mutation Process):

Step 6A: Select a random number (R_2) for mutation of one chromosome.

Step 6B: if R_2 is less than the values of mutation, then apply the mutation process and go to Step 6D.

Step 6C: Else, transfer the chromosome with no mutation.

Step 6D: Repeat Steps 6A to 6C for all chromosomes.

Step 7 (Updating Population):

Replace the old population with the improved population generated by Steps 2 to 6. Check all chromosomes, if there is any chromosome with $F_L=1$, $F_G=1$, $F_V=1$, $F_D=1$ and $F_F > F_{max}$, set $F_{max} = F_F$ and save it. Set $N_{it} = N_{it} + 1$.

Step 8 (Stopping Decisive Factor):

If the maximum number of iterations is achieved, then start PEV charging and go to the next time slot.

IV. ONLINE AND DELAYED (PARTIAL-OVERNIGHT AND FULL-OVERNIGHT) PEV CHARGING USING OL-CC-GA

The proposed OL-CC-GA of Section III is modified to allow for both online and delayed PEV coordination strategies:

- Online Coordination- Vehicles are charged as soon as possible as they are being randomly plugged-in. This will result in high customer satisfaction at higher energy prices.
- Delayed Full-Overnight Coordination- Vehicle charging is delayed and performed during early morning hours to reduce charging cost. This may result in less customer satisfaction as some PEVs may not be fully charged overnight for the next trip.
- Delayed Partial-Overnight Coordination- Some PEVs (e.g., high priority vehicles) are charged quickly as soon as being plugged-in while the rest are postponed for overnight charging.

To implement the above three charging strategies, the information of the randomly arriving PEVs including their plug-in time and locations are stored in the PEV-Queue Table.

PEV charging will start and end at designated off-peak load hours while the maximum demand level is set according to total number of PEVs in the PEV-Queue Table.

To allow for delayed PEV charging, the value of $D_{max}(t)$ in Eq. 2B is modified. For delayed full-overnight charging $D_{max}(t)$ is a constant and is computed by trial and error; $D_{max}(t) = D_{overnight} = 31.1 \text{ kW}$. For delayed partial-overnight charging, $D_{max}(t)$ is computed using the following linear equations:

$$\begin{cases} D_{max}(t) = 43.73(0.85 - 0.025 \times (t - 12:00)); & 06:00^{PM} \leq t < 11:59^{PM} \\ D_{max}(t) = 43.73(0.65 - 0.025 \times (t - 8:00)); & 00:00^{AM} \leq t \leq 08:00^{AM} \end{cases} \quad (7)$$

where the peak load for this test system is 43.73 kW.

V. SIMULATION RESULTS AND DISCUSSIONS

The 19 bus 415V distribution test system of Fig. 4 populated with PEVs is used to evaluate the performance and accuracy of the proposed GA methods. System data including lines and residential loads' parameters are available in [13].

Simulations are performed on the 19- node test feeder of Fig. 4 considering uncoordinated and coordinated PEV charging scenarios. Simulation results for a time slot of $\Delta t = 5 \text{ min}$ are presented in Figs. 5-6 and Table I.

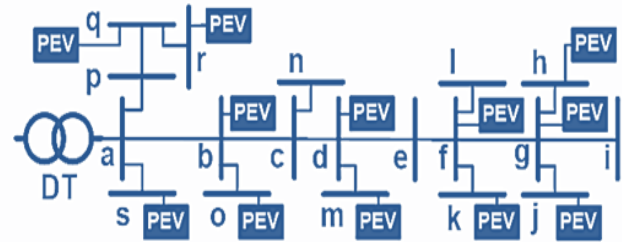


Fig. 4. The 19- node 415V residential feeders with PEVs [13].

A. Uncoordinated PEV Charging

Uncoordinated PEV charging is investigated by simulating a practical scenario with random distribution of PEV charging loads. Simulation results are shown in Figs. 5 (a-c) and Table I (rows 4-5) from which a significant increase in power demand, power generation, voltage deviations and power losses can be observed during the peak load hours. This could cause suboptimal and expensive generation dispatching.

As expected, the SG is facing overloading, voltage regulation and efficiency problems. For example, for 100% PEV penetration, maximum power consumption, maximum system losses and cost have increased by about 89% (Fig. 5(a)), 247% (Fig. 5(c)) and 110% (Fig. 5(b)), respectively; compared to the nominal operation with no vehicles.

B. Coordinated Online (OL-CC-GA) PEV Charging

For further investigations on the performance and accuracy of the uncoordinated charging, the online PEV coordination strategy based on GA is proposed. Simulation results are presented in Fig. 5 and Table I (rows 6-7). Compared to Case A, GA is offering further reduction in transformer overloading (Fig. 5(a)), maximum generation cost level (Reduced from 5.68\$ (Fig.5 (b)) to 2.68\$ (Fig. 5(b))) and maximum system losses (Reduced from 3.27KW to 1.12KW), as well as the total cost (Reduced from 46.31\$/day to 42.44\$/day).

C. Coordinated Delayed Partial-Overnight PEV Charging

The proposed OL-CC-GA is modified to allow for delayed partial-overnight PEV charging using Eq. 7. Simulation results are shown in Fig.6 and Table I (rows 8-9). The performance of partial-overnight PEV charging is different from the uncoordinated and online strategies. Total system losses are significantly reduced compared to case B while voltage fluctuations are still within the 10% limit and the system power consumptions are less than the maximum demand level.

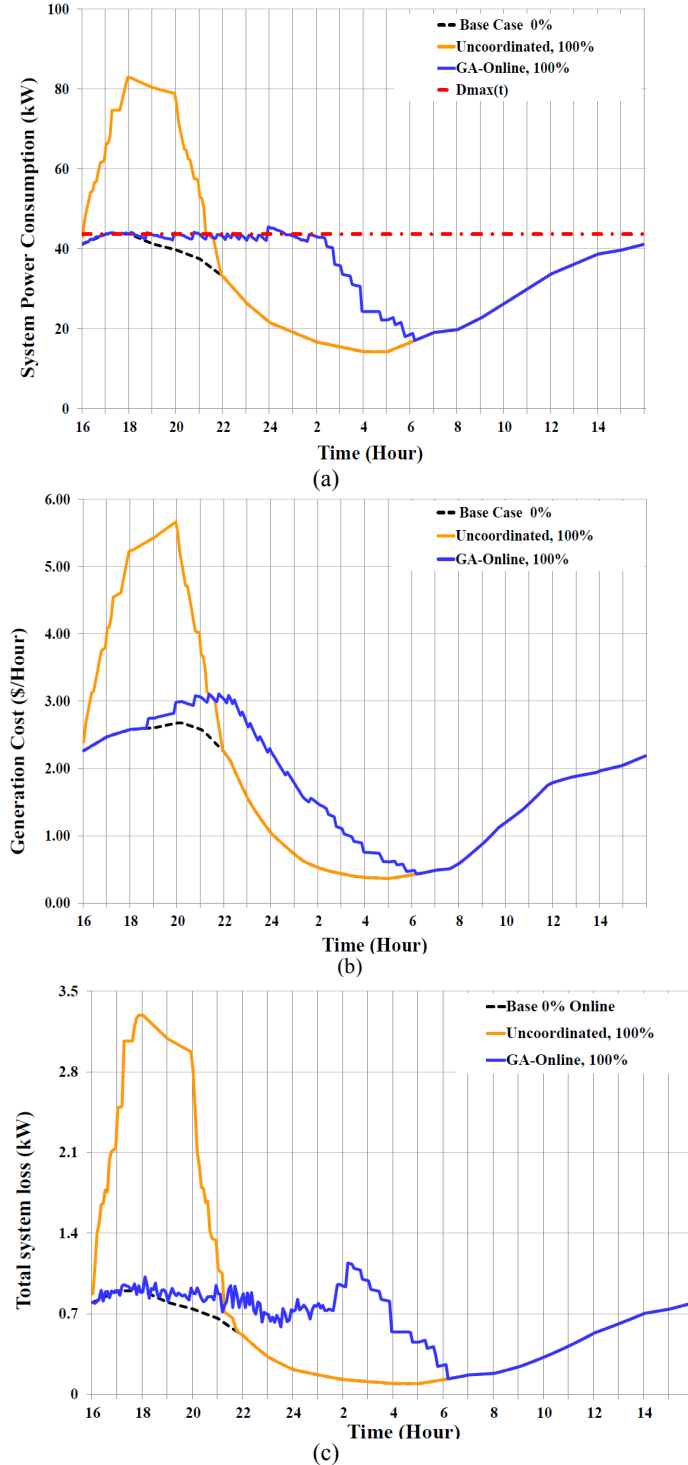


Fig. 5. Simulation results for Cases A-B with 0% and 100% PEV penetrations; (a) system power consumption, (b) generation cost, (c) total system losses.

D. Coordinated Full-Overnight PEV Charging

In this case it is considered that all PEVs will be in the queue and the aggregator will coordinate charging overnight and all PEVs will be fully charged by 8:00 am. To modify OL-CC-GA for full-overnight PEV charging, $D_{max}(t)$ is a constant and its value is computed by trial and error to be $D_{overnight} = 31.1\text{kW}$. The performance of full-overnight PEV charging is better than Cases A-C as the total system losses are significantly reduced and voltage fluctuations are still within the 10% limit.

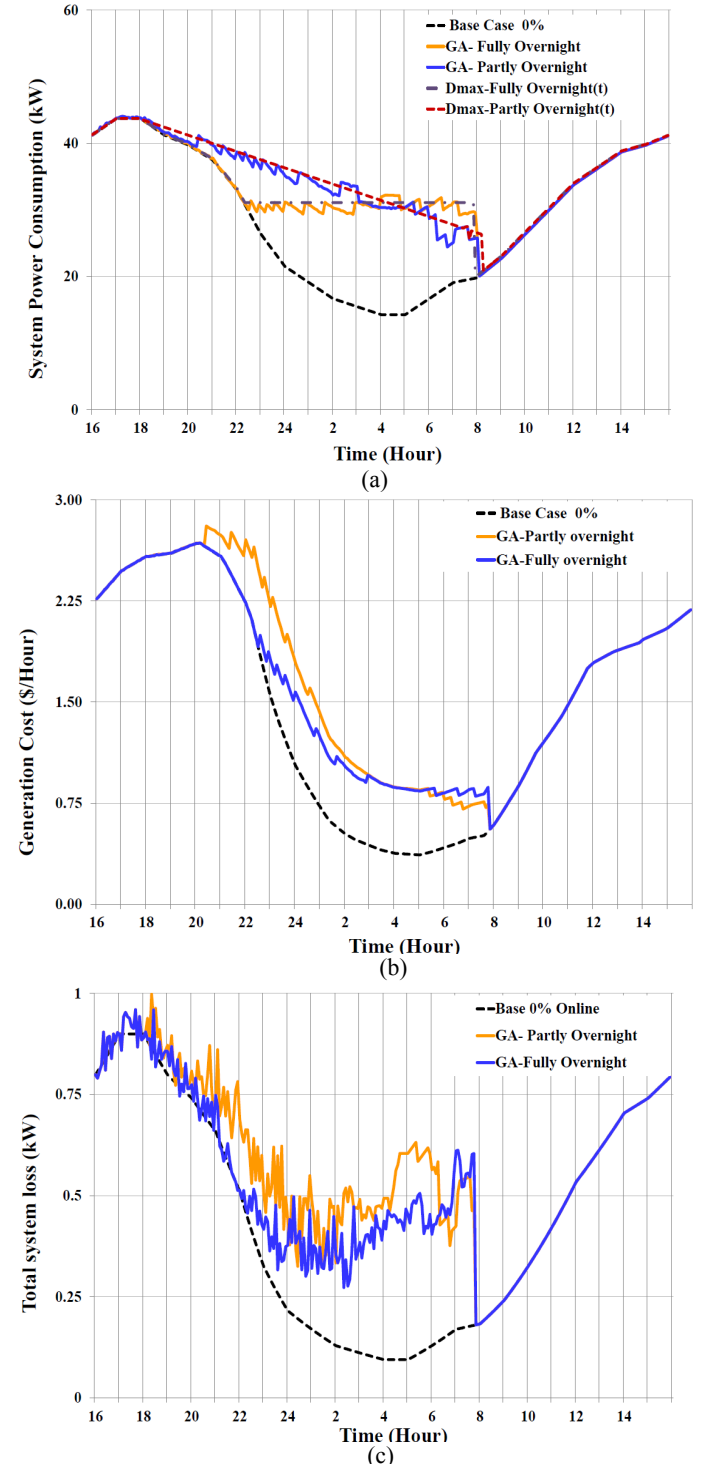


Fig. 6. Simulation results for Cases C-D with 0% and 100% PEV penetrations; (a) system power consumption, (b) generation cost, (c) total system losses.

VI. CONCLUSION

- An online coordinated charging genetic algorithm (OL-CC-GA) for PEVs in SG that can also perform delayed (e.g., partial-overnight or full-overnight) vehicle charging by reducing the distribution transformer loading. Detailed simulation results for a 19-node test feeder are presented and compared with uncoordinated, online, delayed partial-overnight and delayed full-overnight PEV charging. Main conclusions are:
- The proposed OL-CC-GA schedules the charging activities of randomly arriving PEVs at each time slot based on smart meter information using online cost minimization. The modified OL-CC-GA takes advantage of the expert knowledge to vary the distribution transformer loading level ($D_{max}(t)$ in Eq. 2B) and perform delayed PEV charging by postponing some vehicle charging such that the peak power consumption is shifted to the early morning hours to achieve further reductions in total costs as compared to online coordination strategy.
- In OL-CC-GA, the total system cost has the maximum value among three cases B, C and D; however, all PEVs will be charged before 6:00 am. In addition, case B has the maximum losses among all coordinated cases, while the generation cost has the minimum value in case D to compare with the other cases.
- In delayed partial-overnight PEV charging coordination, the generation cost is higher than case D and less than case B.

TABLE I

Impact of uncoordinated, online coordinated (OL-CC-GA) and delayed coordinated PEV charging on the test feeder of Fig. 4.

PEV [%]	ΔV^* [%]	I_{MAX}^{**} [%]	Generation cost [\$/day]	Total cost [\$/day]	Increase in Total cost [%]
Nominal Case: With no PEV (0% PEV penetration)					
0	7.63	0	35.13	36.6	0
Case A: Uncoordinated PEV Charging; Fig. 5					
100	16.10	89	46.31	49.75	26.53
Case B: Online PEV Charging (OL-CC-GA); Fig. 5					
100	9.89	0	42.44	44.93	15.95
Case C: Partial-Overnight PEV Charging (Modified OL-CC-GA); Fig. 6					
100	9.78	0	41.06	43.37	12.18
Case D: Full-Overnight PEV Charging (Modified OL-CC-GA); Fig. 6					
100	9.72	0	40.20	42.18	9.83

*) Average voltage deviation over 24 hours (Eq. 2).

**) Increase in transformer current compared with the nominal case.

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