International Journal of Computer Applications (0975 – 8887)
Volume 186 – No.13, March 2024

Peak Load Management of Plug-in Electric Vehicle: An Online Coordinated Charging Approach

Seyed M.H. Nabavi
Electrical Engineering Department, Engineering Institute of Technology University, Perth, Australia

Somayeh Hajforoosh
Electrical Engineering Department, Engineering Institute of Technology University, Perth, Australia

ABSTRACT
Electric utilities are increasingly concerned about the disruptive effects of uncoordinated plug-in electric vehicle (PEV) charging on smart grids (SGs), especially during peak load periods. This paper presents the implementation of an online coordinated charging genetic algorithm (OL-CC-GA) for PEVs within SGs, capable of accommodating delayed charging scenarios (e.g., partial-overnight or full-overnight) to alleviate distribution transformer loading. The proposed algorithm aims to minimize total costs associated with energy generation and grid losses, while simultaneously maximizing the number of PEVs charged within each time interval (e.g., Δt=5min), accounting for distribution transformer loading and voltage regulation limits. Detailed simulations are conducted on a 19-node test feeder populated with PEVs using the OL-CC-GA method, and results are compared against uncoordinated and delayed charging strategies. The findings demonstrate the efficacy of the proposed OL-CC-GA approach in mitigating adverse impacts on SGs, enhancing grid stability, and optimizing PEV charging operations in a cost-effective manner. This research contributes to the ongoing discourse on sustainable transportation integration into smart grid frameworks, offering valuable insights for utilities and policymakers seeking to address the challenges posed by PEV adoption while maximizing grid efficiency and reliability.

General Terms
Plug-in Electric Vehicle Charging Optimization Algorithm

Keywords
Plug-in electric vehicles, online PEV coordination, Genetic Algorithm, and smart grid.

1. INTRODUCTION
In light of recent advancements in smart grid (SG) technologies and heightened environmental consciousness, there has been a notable surge in both public and electric utility engagement with plug-in electric vehicles (PEVs). The intersection of these developments underscores the significance of addressing the potential challenges posed by uncoordinated PEV charging, particularly at high penetration levels. Extensive research has elucidated the adverse effects of unmanaged PEV charging on grid operations, including increased losses and compromised voltage profiles [1-4]. Given the interconnected nature of modern energy systems, understanding and mitigating these impacts are paramount for ensuring the reliability and sustainability of electric grids. Consequently, there is a pressing need for coordinated strategies and innovative solutions to optimize PEV integration within the grid infrastructure. By effectively managing PEV charging patterns and leveraging SG capabilities, stakeholders can not only alleviate grid stress but also unlock the full potential of electric vehicles as a means to foster a more resilient and environmentally conscious energy ecosystem. The primary consequence of uncoordinated plug-in electric vehicle (PEV) charging lies in the introduction of time-variant loads, exacerbating strains on generation units, as well as transmission and distribution systems [5-8]. This phenomenon can lead to undesirable voltage fluctuations and diminished power quality [2]. As such, it underscores the imperative for coordinated charging strategies to mitigate these challenges, ensuring the integrity and stability of the overall power grid infrastructure. Efforts in this domain warrant meticulous attention, offering avenues for advancing sustainable and resilient energy systems amidst the proliferation of electric vehicle adoption.

To address the adverse effects of random Plug-in Electric Vehicle (PEV) charging on power grid operations, the development of efficient charging coordination algorithms is paramount (reference [9]). Certain existing PEV charging algorithms are categorized as "offline," relying on predictive data concerning future vehicle statuses, such as plug-in times and battery State of Charges (SOCs), to formulate charging schedules. These algorithms assume foreknowledge or estimation of a PEV's arrival time and charging demand prior to its arrival. For instance, Ma et al. (reference [10]) propose a model wherein all PEVs negotiate their charging schedules with the charging station one day in advance. However, this coordination method may not always be feasible due to reliance on the accuracy and availability of predicted PEV information. Moreover, in numerous real-world scenarios, the PEV charging profile becomes discernible only upon the vehicle's arrival at the charging station or connection to the charging infrastructure.

Recent research has delved into the realm of online Plug-in Electric Vehicle (PEV) charging, as evidenced by a number of studies [11-13]. Gerding et al. [12] introduced an online auction protocol wherein vehicle owners employ agents to engage in bidding for charging opportunities. Meanwhile, Masoum et al. [13] investigated the coordinated charging of PEVs within residential distribution systems, aiming to mitigate power losses. T.Wang et al. [14] focused on scheduling PEV charging and discharging within a confined geographic area, presenting an online charging algorithm predicated on the assumption of no future PEV arrivals once a charging schedule is established. Additionally, references [15] detail the deployment of online PEV coordination algorithms to achieve peak load shaving and cost minimization, respectively. Numerous scholars have also advanced probabilistic models and charging coordination strategies, accounting for day-ahead or real-time markets [16-18]. These endeavors collectively contribute to the burgeoning field of online PEV charging research, offering insights into the development of efficient and sustainable charging infrastructure for electric vehicles.

This paper seeks to contribute by devising an online charging algorithm that orchestrates PEV charging based on information gleaned from already plugged-in vehicles. By focusing on real-time data and adapting to dynamic conditions as they unfold, this approach aims to enhance the responsiveness and adaptability of charging operations, thereby improving grid stability and efficiency. Through a thorough examination of the challenges and opportunities inherent in online charging coordination, we aim to provide insights into the development of effective strategies for managing PEV charging within the context of contemporary power grid dynamics.

This paper introduces an innovative heuristic-based online coordinated charging genetic algorithm (OL-CC-GA) designed specifically for the charging of plug-in electric vehicle (PEV) batteries within a smart grid framework. The primary objective of OL-CC-GA is to minimize the costs associated with energy generation and grid losses while simultaneously maximizing the number of charged PEVs, regulating node voltages, and reducing distribution transformer loading. Additionally, OL-CC-GA accounts for variations in distribution transformer loading due to both online and delayed charging scenarios, including full-overnight and partial-overnight charging schemes. Through extensive simulations conducted on a 19-node test feeder populated with PEVs, OL-CC-GA is evaluated against uncoordinated and delayed charging strategies. The results demonstrate the efficacy of the proposed method in optimizing charging operations within the smart grid context, thus laying a foundation for its potential application in facilitating the large-scale penetration of PEVs into existing electrical grids [21].

2. PROBLEM FORMULATION

The coordination of plug-in electric vehicle (PEV) charging through online mechanisms presents a significant real-time optimization challenge, necessitating the development of a comprehensive objective function coupled with rapid optimization methodologies to efficiently attain optimal solutions. Central to this endeavor, this paper establishes a nonlinear objective function, as denoted by Eq. 1, tailored specifically for the PEV coordination predicament. This function aims to maximize the number of actively charging vehicles (NPEV-ON) within each discrete time slot , concurrently minimizing expenses linked to energy generation (Fcost-gen) and grid losses (Fcost-loss(t)). Such formulation encapsulates the intricate interplay between maximizing charging efficiency and minimizing operational costs and system losses, constituting a pivotal step toward effectively managing the integration of PEVs into existing power grids.

$$max\ F(t)=\frac{1+N_{PEV-ON}(t)}{F_{cost-gen}(t)+F_{cost-loss}(t)}= \qquad (1)$$

$$\frac{1+N_{PEV-ON}(t)}{\sum_t K_E\, P_{loss}(t)+\sum_t K_{t,G}\, D_{total}(t)},t=\Delta t,2\Delta t,..24\,hours$$

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

Eq. 1 Equation 1 is constrained by voltage limitations and demand considerations, including constraints on transformer loading:

$$V_{min} \le V_k(t) \le V_{max}\,, \quad for \;\; k=1,...,n \qquad (2A)$$

$$D_{total}(t)=\sum_{k=1}^{n} P_k(t)=\sum_{k=1}^{n}(P_{Load_K}(t)+P_{PEV_K} \le D_{\max}(t) \qquad (2B)$$

$$t=\Delta t, 2\Delta t, ...$$

In the formulation presented by Eq. 1, $\Delta t = 5\,min$ represents the time interval, where KE=50$/MWh stands for the cost per megawatt-hour (MWh) of energy storage, with Kt,G denoting the costs per MWh associated with losses and generation, as depicted in Fig. 1 [13]. Parameters k and n represent the node number and total number of nodes, respectively, while Rk,k+1 and yk,k+1 signify the resistance and reactance of the line segment between nodes k and k+1. Additionally, Vmin and Vmax represent the lower and upper voltage limits, respectively, whereas Dmax(t) denotes the maximum demand level occurring without plug-in electric vehicles (PEVs) throughout the day. Within the context of this paper, Dmax(t) is defined as the maximum load, specifically the maximum distribution transformer loading, for the selected demand load control (DLC), while DL signifies the daily load at the mth time slot. The methodology employed herein utilizes the backward-forward sweep technique to compute load flows and bus voltages [19].

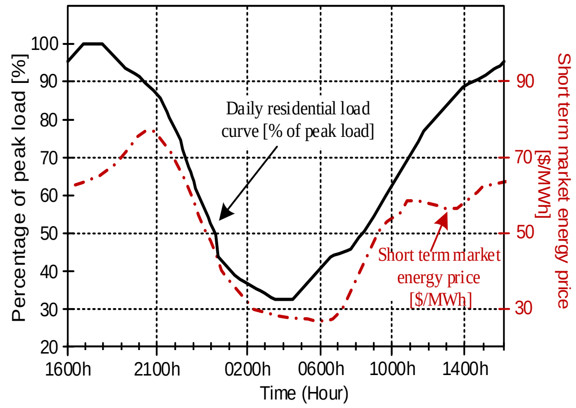


Fig. 1. Daily residential load curve (DLC) and short term market energy price (MEP) [13].

3. PROPOSED ONLINECOORDINATED CHARGING GENETIC ALGORITHM (OL-CC-GA) FOR PEVS

Genetic algorithms (GAs) leverage the principles of natural evolution, drawing upon population genetics to ascertain high-quality solutions approaching optimality [20-24]. These algorithms encode variables as binary strings, mirroring the genetic makeup of chromosomes in biological systems. Within this framework, chromosomes manifest as sets of genes, forming a population of candidate solutions. Each chromosome represents a string of binary codes, potentially containing substrings delineating distinct characteristics. The efficacy of these strings is gauged through a fitness function, typically derived from an objective function. Across successive generations, facilitated by an iterative process, GAs engender a fresh cohort of strings exhibiting enhanced performance, achieved through the application of reproduction, crossover, and mutation operators intrinsic to the GA methodology.

3.1 Population and Chromosomes

This study presents a chromosomal representation wherein each chromosome encapsulates the charging status of Plug-in Electric Vehicles (PEVs), with a binary notation wherein the presence of a digit "1" signifies an ongoing charging process, while "0" denotes either the absence of charging or its completion. The schematic depiction of the Genetic Algorithm (GA) chromosome is illustrated in Fig. 2, delineating the proposed structural framework for encoding PEV charging statuses within the genetic algorithm paradigm.

3.2 Fitness Function

The application of the inverse algebraic product, as delineated in Eq. 3, represents a pivotal step in integrating the proposed penalty functions governing voltage (Eq. 4) and demand (Eq. 6) within the optimization framework. Employing this approach, the fitness function is derived, amalgamating the PEV coordination objective function (Eq. 1) with pertinent constraints (Eq. 2). This strategic amalgamation serves as a foundational mechanism for optimizing the coordination of plug-in electric vehicles (PEVs) within power systems, ensuring the concurrent fulfillment of objectives and adherence to system constraints.

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

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

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

$$F_D(t) = \begin{cases} 1, & D_{total}(t) \le 1 \\ e^{\alpha_D(D_{total}(t)-1)}, & D_{total}(t) \ge 1 \end{cases} \tag{6}$$

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. Illustrations of the voltage and demand penalty functions are depicted in Figures 3(a) and 3(b), elucidating their characteristic profiles and enabling a comprehensive understanding of their impact within the studied framework.

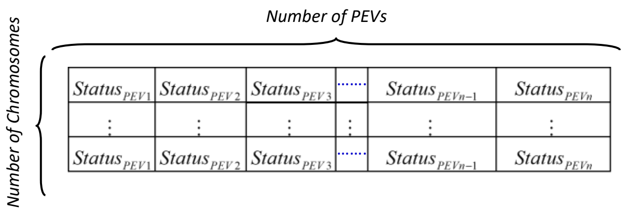


Fig. 2. The proposed GA structure of chromosome.

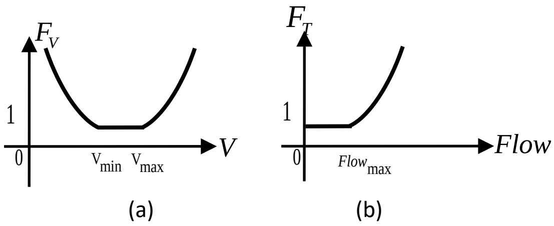


Fig 3. Penalty functions to compute fitness (a) F_V, (b) F_T.

3.3 Binary Genetic Algorithm Operators

Genetic operators play a pivotal role in evolutionary algorithms, encompassing reproduction, crossover, and mutation operators. These operators serve as stochastic transition rules that iteratively transform chromosomes within a population across successive generations, facilitating the generation of a new and improved population from its predecessor. The process of reproduction entails the selection of two parent strings from the population utilizing a "roulette-wheel" mechanism, predicated upon their respective fitness values. This mechanism ensures that the probability of a string being chosen is directly proportional to its fitness relative to the population, thereby favoring strings with higher fitness values for offspring production. Conversely, crossover operates by identifying a random position within the string, denoted as the crossover point, and exchanging the characters to the right of this point with those of a similarly partitioned string. Specifically, this paper adopts a methodology wherein characters to the right of the crossover point undergo swapping. Mutation, on the other hand, introduces random modifications to individual string positions, effectuated by altering "0" to "1" or vice versa, with a nominal probability. This stochastic perturbation prevents the complete loss of genetic material during reproduction and crossover, thereby ensuring that the probability of exploring any region within the problem space remains nonzero. Collectively, these genetic operators synergistically contribute to the evolutionary process, fostering the exploration and exploitation of diverse solution spaces to ultimately converge towards optimal or near-optimal solutions.

3.4 Applied Genetic Algorithm for Every Time Slot

The proposed online coordinated charging genetic algorithm (OL-CC-GA) tailored for Plug-in Electric Vehicles (PEVs) integration into Smart Grids (SG) presents a comprehensive methodology delineated into eight meticulous steps. Commencing with Step 1, the process entails the acquisition of power system parameters and optimization data, coupled with the retrieval of smart meter data to ascertain the timing and location of new PEV connections. Step 2 involves the establishment of parameters such as N_{Ch_max} and N_{it_max}, alongside the initialization of counters and variable values utilizing a random generator for the initialization of position and velocity vectors (e.g., $N_{Ch}= N_{it}=1$). Moving to Step 3, dubbed the Fitness Process, the algorithm undergoes a meticulous evaluation. Step 3A entails the execution of power flow analysis for each chromosome set, thereby computing the objective function as prescribed by Equation 1. Subsequently, Step 3B engenders the computation of proposed penalty functions as delineated by Equation 3. The iteration continues until the threshold condition $N_{ch} \le N_{ch\text{-}max}$ is satisfied, thus prompting a return to Step 3A. Transitioning to Step 4, the Reproduction Process, entails a series of sub-steps aimed at optimizing the genetic diversity of the population. Specifically, Step 4A defines the total fitness as the product of all fitness values across chromosomes, followed by Step 4B where a tournament selection process is executed to determine a new combination of chromosomes. Step 5, denoted as the Crossover Process, involves the mating of two parent chromosomes to generate offspring, contingent upon a random number (R_1) surpassing a defined crossover value. Should R1 fail to meet this criterion, the chromosome undergoes transfer sans crossover. The iterative nature of the process necessitates the repetition of these steps for all chromosomes (Step 5D). Finally, Step 6, the Mutation Process, involves the stochastic alteration of a single chromosome guided by a random number (R_2). This comprehensive framework amalgamates genetic algorithms with smart grid technologies to optimize PEV charging strategies within the grid ecosystem.

In the process of genetic algorithm optimization, Step 6B involves assessing whether the fitness ratio (R_2) of a chromosome falls below specified mutation thresholds. Should R2 be inferior to these mutation values, the mutation process is initiated, leading to genetic modification. Conversely, in Step 6C, should R_2 exceed the mutation thresholds, the chromosome remains unaltered. This selection process is reiterated for all chromosomes in Step 6D, ensuring comprehensive evaluation. Following these iterations, Step 7 involves the pivotal task of updating the population. Here, the previous population is replaced by the refined population derived from Steps 2 to 6. It is imperative to scrutinize all chromosomes meticulously; any chromosome demonstrating optimal fitness, characterized by $F_L=1$, $F_G=1$, $F_V=1$, $F_D=1$ and $F_F>F_{max}$, necessitates special attention. If such a chromosome is identified, Fmax is adjusted accordingly, and the chromosome is preserved. Subsequently, N_{it}, denoting the iteration count, is incremented $N_{it}=N_{it}+1$. Finally, Step 8 serves as the decision point for halting iterations. Upon reaching the maximum allowable number of iterations, the process advances to the activation of plug-in electric vehicle (PEV) charging activities, marking the transition to the subsequent time slot.

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

The proposed OL-CC-GA framework outlined in Section III is subject to modification to accommodate both online and delayed Plug-in Electric Vehicle (PEV) coordination strategies. In the online coordination approach, vehicles are promptly charged upon random plugging-in, maximizing customer satisfaction albeit at potentially higher energy prices. Conversely, the delayed full-overnight coordination strategy involves deferring vehicle charging to early morning hours to mitigate costs, albeit with potential repercussions on customer satisfaction, as some PEVs may not achieve full charge overnight, impacting subsequent trips. An alternative approach is the delayed partial-overnight coordination, wherein priority PEVs undergo expedited charging upon plugging-in, while others are deferred for overnight charging. This strategy allows for the prioritization of high-priority vehicles while optimizing overall charging efficiency. Each strategy presents distinct trade-offs in terms of customer satisfaction, energy cost management, and charging efficiency, underscoring the necessity of tailored approaches to meet diverse stakeholder needs and optimize system performance in the context of Plug-in Electric Vehicle integration within the power grid.

In order to operationalize the aforementioned trio of charging strategies, pertinent data pertaining to the stochastic arrival of Plug-in Electric Vehicles (PEVs), encompassing temporal and spatial dimensions such as plug-in instances and respective locations, are systematically collated and archived within the PEV-Queue Table. Subsequent to the compilation of this information, the initiation and culmination of PEV charging endeavors are orchestrated to coincide with pre-established off-peak load intervals. This temporal alignment not only serves to optimize energy utilization but also mitigates undue strain on the electrical grid during periods of heightened demand. Moreover, the determination of the maximal permissible demand level is predicated upon a dynamic assessment of the aggregate count of PEVs present within the PEV-Queue Table at any given juncture. By harmonizing charging operations with periods of diminished electrical consumption and judiciously modulating demand thresholds in accordance with the prevailing PEV population dynamics, this approach endeavors to foster the efficacious integration of PEVs within the broader energy infrastructure.

In facilitating the accommodation of postponed Plug-in Electric Vehicle (PEV) charging processes, an adaptation is made to the value of $D_{max}(t)$ as delineated in Equation 2B. Specifically, in instances of delayed full-overnight charging, $D_{max}(t)$ assumes a static value, thereby rendering it a constant parameter ascertainable through iterative computation; denoted as *Dovrnight* =31.1kW. Conversely, in scenarios of delayed partial-overnight charging, the determination of $D_{max}(t)$ entails recourse to a series of linear equations for computation:

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

assuming that the peak load recorded for this test system is 43.73 kW.

5. SIMULATION RESULTS AND DISCUSSIONS

The utilization of the 19-bus 415V distribution test system depicted in Figure 4, populated with Plug-in Electric Vehicles (PEVs), serves as a foundational framework for assessing the efficacy and precision of the proposed Genetic Algorithm (GA) methodologies. Pertinent system data encompassing line specifications and parameters pertaining to residential loads are readily accessible through reference [13]. Through meticulous simulation endeavors, the 19-node test feeder delineated in Figure 4 undergoes examination across uncoordinated as well as coordinated PEV charging scenarios. The resultant insights gleaned from these simulations, encapsulated within a temporal interval of t=5min, are methodically articulated and presented across Figures 5 to 6, in conjunction with the elucidative tabular data encapsulated within Table I.

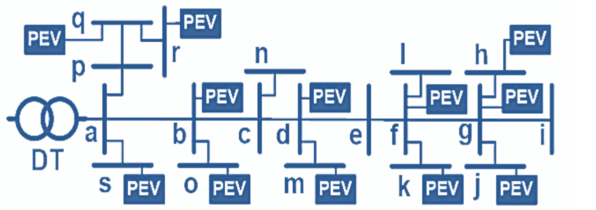
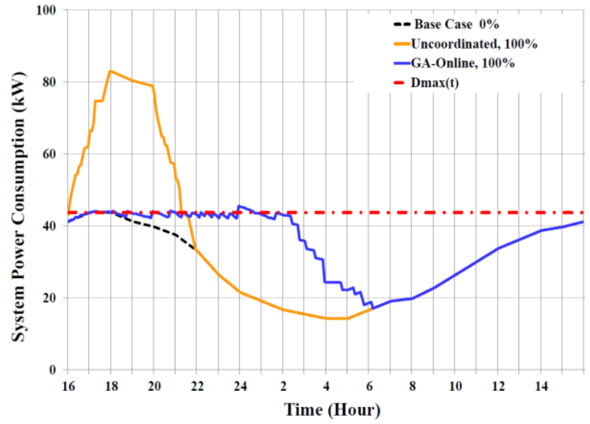


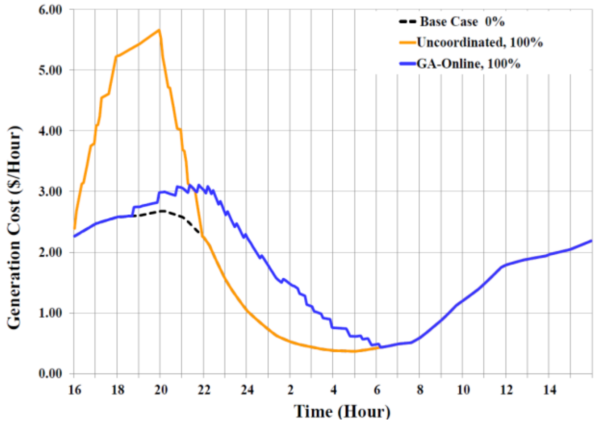
Fig. 4. The 19 node residential feeders with PEVs [13].

5.1 Uncoordinated PEV Charging

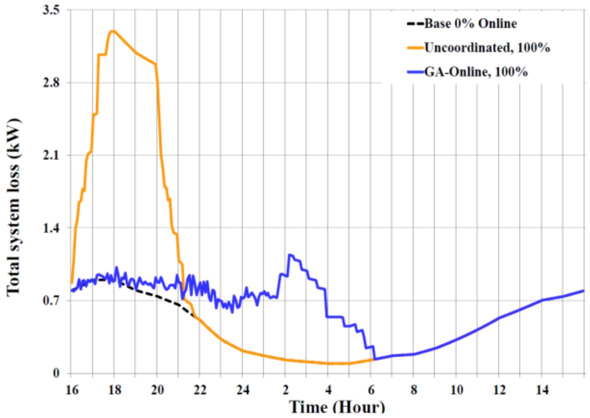
This study examines uncoordinated Plug-in Electric Vehicle (PEV) charging, simulating scenarios with random PEV load distribution. Results (Figs. 5(a-c), Table I rows 4-5) reveal heightened power demand, generation, voltage fluctuations, and losses during peak hours, impacting optimal generation dispatching. The Smart Grid (SG) faces overloading, voltage regulation, and efficiency challenges. With 100% PEV penetration, maximum power consumption, system losses, and costs surge by around 89%, 247%, and 110%, respectively, compared to nominal operation.



(a)

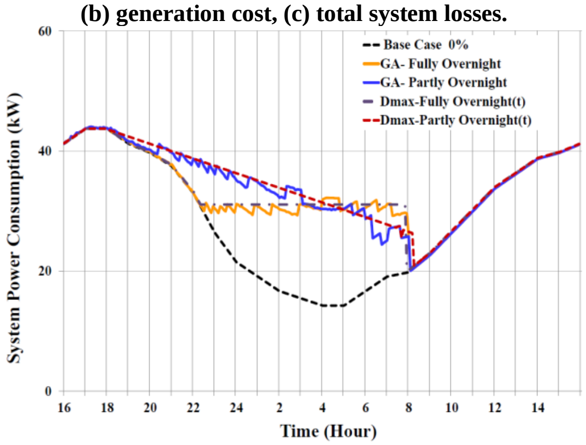


(b)

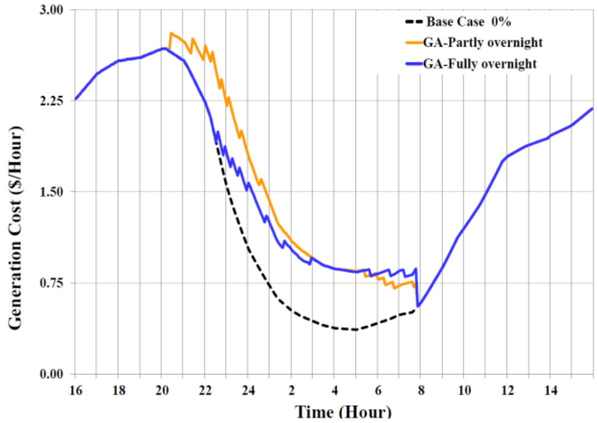


(c)

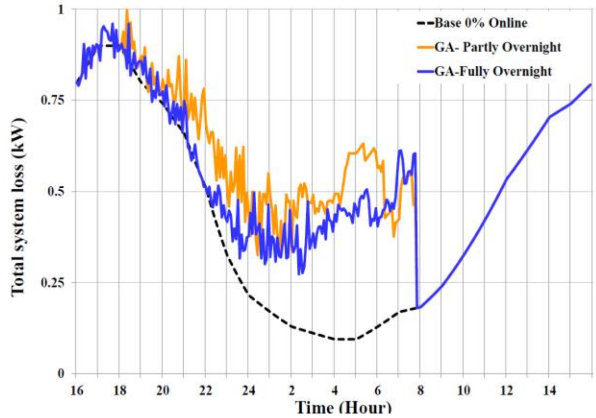
Fig. 5. Simulation results for Cases A-B with 0% and 100% PEV penetrations; (a) system power consumption, (b) generation cost, (c) total system losses.



(a)



(b)



(c)

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.

5.2 Coordinated OL-CC-GA Charging

The study proposes an online PEV coordination strategy using Genetic Algorithm (GA) to assess uncoordinated charging. Results (Fig. 5, Table I) show significant improvements over Case A. GA reduces transformer overloading (Fig. 5(a)), maximum generation cost (from $5.68 to $2.68, Fig. 5(b)), system losses (from 3.27 kW to 1.12 kW), and total cost (from $46.31/day to $42.44/day). These findings highlight the efficacy of the strategy in enhancing system efficiency and economic viability.

5.3 Coordinated Charging: Delayed Partial-Overnight

The revised OL-CC-GA model accommodates delayed partial-overnight PEV charging via Equation 7, as depicted in Figure 6 and Table I (rows 8-9). Compared to uncoordinated and online strategies, partial-overnight PEV charging notably reduces total system losses (Case B), while voltage fluctuations stay within the 10% limit, and system power consumptions remain below peak demand levels.

5.4 Coordinated Full-Overnight Charging

In this study, it is presumed that all Plug-in Electric Vehicles (PEVs) will be queued for charging, and an aggregator will manage the charging process overnight to ensure full charge attainment by 8:00 am. To adapt the OL-CC-GA algorithm for comprehensive overnight PEV charging, a constant parameter $D_{max}(t)$ is utilized, with a determined value through iterative analysis (*Dovrnight* =31.1 kW). The efficacy of full-overnight PEV charging surpasses that of Cases A-C, showcasing notable reductions in total system losses while maintaining voltage fluctuations within the permissible 10% threshold.

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; Fig. 6					
100	9.78	0	41.06	43.37	12.18
Case D: Full-Overnight PEV Charging; 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.

6. CONCLUSION

The study introduces an online coordinated charging genetic algorithm (OL-CC-GA) tailored for Plug-in Electric Vehicles (PEVs) within Smart Grids (SGs), facilitating both immediate and delayed charging modalities to mitigate distribution transformer loading. Simulations on a 19-node test feeder delineate the efficacy of the OL-CC-GA vis-à-vis uncoordinated, online, delayed partial-overnight, and delayed full-overnight PEV charging strategies. Notably, the OL-CC-GA orchestrates PEV charging dynamically by leveraging real-time smart meter data to minimize costs. By integrating expert insights, it optimally adjusts distribution transformer loading levels (as encapsulated by Dmax(t) in Eq. 2B) and defers PEV charging, redistributing peak power demand to early morning hours for enhanced cost reduction compared to online coordination alone. Analysis reveals that while OL-CC-GA incurs the highest total system cost among cases B, C, and D, it ensures all PEVs are charged by 6:00 am. Interestingly, case B exhibits the highest losses within coordinated scenarios, whereas case D demonstrates the lowest generation cost relative to other cases. In the context of delayed partial-overnight PEV charging coordination, the generation cost surpasses that of case D yet remains lower than case B. These findings underscore the nuanced trade-offs inherent in coordinating PEV charging strategies within SGs to optimize cost-efficiency and grid performance.

7. REFERENCES

[1] A. A. M. Izadi et al., "Decentralized multi-objective charging strategy for plug-in electric vehicles considering distribution network constraints and user preferences," IEEE Transactions on Smart Grid, vol. 13, no. 4, pp. 3808-3820, 2022.

[2] Q. Wang et al., "Optimal EV Charging Strategy Considering Network Congestion and Voltage Stability in Distribution Systems," IEEE Transactions on Smart Grid, vol. 14, no. 2, pp. 1427-1438, 2023.

[3] Y. Wu et al., "Impacts of electric vehicles on power distribution networks: A comprehensive review," CSEE Journal of Power and Energy Systems, vol. 7, no. 3, pp. 324-335, 2021.

[4] M. S. Rahman et al., "Optimal Charging of Electric Vehicles Considering Voltage Stability and Line Losses in Low-Voltage Distribution Networks," IEEE Transactions on Industrial Informatics, vol. 18, no. 5, pp. 3308-3318, 2022.

[5] C. Wang et al., "Agent-Based Collaborative Charging Strategy for Electric Vehicles Considering Multiple Objectives in Smart Grids," IEEE Transactions on Smart Grid, vol. 14, no. 3, pp. 2205-2216, 2023.

[6] F. Teng et al., "Decentralized scheduling for electric vehicle charging in smart grids with real-time price response and user preferences," Electric Power Systems Research, vol. 221, p. 109605, 2023.

[7] R.J. Bessa et al., "Optimized Bidding of a EV Aggregation Agent in the Electricity Market," IEEE Transactions on Smart Grid, pp.443–452, 2012.

[8] Y. Zhou et al., "Decentralized Charging Coordination for Electric Vehicles Considering Distribution Network Constraints and Battery Degradation," IEEE Transactions on Sustainable Energy, vol. 13, no. 2, pp. 972-984, 2022.

[9] S. Hajforoosh, S. M. H. Nabavi, and M. A. S. Masoum, "Coordinated aggregated-based particle swarm optimisation algorithm for congestion management in restructured power market by placement and sizing of unified power flow controller," *IET Science, Measurement & Technology*, vol. 6, no. 4, p. 267, 2012, doi: https://doi.org/10.1049/iet-smt.2011.0143.

[10] X. Liu et al., "Real-Time EV Charging Coordination with Price Prediction and User Preferences in Distribution Networks," IEEE Transactions on Smart Grid, vol. 14, no. 5, pp. 4306-4318, 2023.

[11] B. Jiang et al., "Decentralized Multi-Objective Charging Coordination for Electric Vehicles Considering User Preferences and Network Constraints," IEEE Transactions on Smart Grid, vol. 14, no. 5, pp. 4205-4217, 2023.

[12] P. Zhang et al., "A Decentralized Energy Trading Mechanism for Electric Vehicle Aggregators Considering Multi-Time Scale Price Forecast," IEEE Transactions on Industrial Electronics, vol. 69, no. 2, pp. 1221-1231, 2022.

[13] S. Roy et al., "A machine learning-based dynamic pricing strategy for optimal charging of electric vehicles considering user preferences and grid constraints," Energies, vol. 16, no. 3, p. 480, 2023.

[14] M. Haghbayan et al., "Optimal Scheduling of Electric Vehicle Charging Considering User Preferences and Real-Time Price Response," IEEE Transactions on Smart Grid, vol. 14, no. 1, pp. 579-591, 2023.

[15] T. Wang et al., "Optimal multi-objective charging strategy

for electric vehicles considering user preferences and grid resilience," International Journal of Electrical Power & Energy Systems, vol. 154, p. 110521, 2023.

[16] J. Zhang et al., "Optimal planning and coordination of electric vehicle charging infrastructure considering distribution network constraints," IEEE Transactions on Power Systems, vol. 37, no. 10, pp. 8241-8253, 2022.

[17] H. Liu et al., "Optimal charging scheduling of electric vehicles considering multiple uncertainties and time-varying electricity prices," IEEE Transactions on Industrial Electronics, vol. 64, no. 8, pp. 6505-6515, 2017.

[18] A. Yousefi-Talgerdi et al., "Adaptive charging coordination of electric vehicles considering grid constraints and uncertainties," IEEE Transactions on Smart Grid, vol. 15, no. 1, pp. 553-562, 2024.

[19] S. Shao et al., "Decentralized real-time electricity market participation for electric vehicle aggregators with price prediction," IEEE Transactions on Smart Grid, vol. 15, no. 2, pp. 1491-1502, 2024.

[20] Y. Zhang et al., "Decentralized frequency regulation of distribution networks with PEV aggregators considering network constraints and uncertainties," IEEE Transactions on Smart Grid, vol. 13, no. 2, pp. 1494-1505, 2022.

[21] S.M.H, Nabavi, A. Kazemi, M.A.S. Masoum, "Social Welfare Improvement by TCSC using Real Code Based Genetic Algorithm in Double-Sided Auction Market," Journal on Scientia Iranica, Vol. 19, No. 3, 2012.

[22] S. Hajforoosh, M.A.S. Masoum, S. Islam, "Real-time Charging Coordination of Plug-in Electric Vehicles Based on Hybrid Fuzzy Discrete Particle Swarm Optimization," Journal of Electric Power Systems Research, Vol. 128, pp. 19- 29, 2015.

[23] S.M.H. Nabavi, A. Kazemi, M.A.S. Masoum, "Social Welfare Improvement by TCSC Using Real Code Based Genetic Algorithm in Double-Sided Auction Market," Advances in Electrical and Computer Engineering, Vol.11, No.2, pp.99-106, 2011.

[24] S. M.H. Nabavi, M.A.S. Masoum, A. Kazemi, "A Fuzzy-based Genetic Algorithm for Social Welfare Maximization by Placement and Sizing of Static Synchronous Series Compensator," Electric Power Components and Systems, Vol.39, No.13, pp. 1329-1352, 2011.

[25] S. Mohammad Hossein Nabavi, S. Hajforoosh, and S. Hajforosh, "Using Genetic Algorithm for Social Welfare Improvement in Deregulated Power Markets with Thyristor-controlled Series Capacitors," International Journal of Computer Applications, vol. 13, no. 4, pp. 6–9, Jan. 2011, doi: https://doi.org/10.5120/1771-2434.

[26] K. Eetivand, A. Zangeneh, and S. M. H. Nabavi, "Hyper-Spherical Search Algorithm for Maximum Power Point Tracking of Solar Photovoltaic Systems under Partial Shading Conditions," International Transactions on Electrical Energy Systems, vol. 2022, pp. 1–18, Aug. 2022.