Optimized electric vehicle charging allocation with overload management and vehicle to grid support

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ABSTRACT

The rapid proliferation of electric vehicles (EVs) in residential distribution networks poses significant challenges, particularly in managing peak demand and maintaining grid stability during the peak demand periods. This study employs a day-ahead EV charging framework in compliance with valley-filling technique to align charging during off-peak periods for a centralized residential charging station that balances grid stability with customer satisfaction. To mitigate network overloading, vehicle to grid support is integrated through optimization based on genetic algorithm (GA), enabling optimal scheduling of both charging and discharging activities under operational constraints. Simulation outcomes substantiate the efficacy of the proposed charging scheme in preventing overloads and demonstrate a notable enhancement in the load factor from 70.68% to 82.24%, reflecting enhanced utilization of energy resources. The approach offers technical and economic benefits for both utilities and EV users, highlighting its potential for scalable and efficient grid management.

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1. INTRODUCTION

The rapid adoption of electric vehicles (EVs) is being driven by concerns over fossil fuel depletion and the urgent need to reduce greenhouse gas emissions [1]. The transportation sector accounts for nearly a quarter of global energy-related CO_2 emissions, with road transport alone contributing almost 20% [2]. Without substantial mitigation measures, transport-related energy use is projected to double by 2050, leading to significant increases in emissions [3], [4]. As part of the solution, governments worldwide have implemented measures such as subsidies, customs exemptions, and tax rebates to accelerate EV uptake [5], [6]. Consequently, EV sales reached 17.1 million units globally in 2024, representing a 25% year-on-year increase, with China, Europe, and the United States comprising over 90% of the market [7], [8]. While this transition promises substantial environmental benefits, the large-scale integration of EVs into existing residential distribution networks introduces significant technical and operational challenges [9]. The additional and often unpredictable charging demand from a growing EV fleet can substantially alter the traditional load profile, creating new peaks that strain network capacity [10]. Uncoordinated charging can exacerbate peak demand [11], cause transformer overloading [12], degrade power quality [13], increase harmonic distortion [14], and result in voltage drops [15]. To address these issues, two primary charging coordination models have been developed: decentralized charging, where EVs are charged independently at homes, offices, and public facilities, and centralized charging, where a central controller schedule charging across multiple EVs [16]. Although decentralized charging offers high user flexibility, its uncoordinated nature can cause unanticipated load spikes that exceed operational and thermal limits [17]. Centralized coordination, in contrast, enables optimized charging schedules by leveraging real-time grid data, electricity tariffs, and user preferences, and can incorporate vehicle-to-grid (V2G) technology, allowing EVs to discharge energy back to the grid to enhance stability and reliability [18], [19].

In recent years, extensive research has focused on centralized coordination of EV charging, targeting objectives such as cost minimization, overload prevention, and customer satisfaction. For example, [20] presents a stochastic optimization framework to reduce charging costs by considering day-ahead electricity prices, battery degradation, and uncertainties in vehicle arrival/departure times. While effective for cost optimization, this work does not address overload control or user preference integration. Similarly, [21] develops an aggregative game-theoretic model to schedule EV charging while accounting for EV interactions and their influence on electricity prices. However, this approach excludes V2G functionalities and overload mitigation. Other studies have emphasized user engagement and load balancing. In [22], a web application is proposed to collect user energy requirements, manage charging schedules, and prevent overloads by providing feedback on costs and time-slot availability. Despite its usability, V2G integration is absent, limiting its ability to provide bidirectional grid support. A valley-filling technique is employed to shift EV charging loads based on a priority factor, effectively reducing overload but risking customer dissatisfaction due to potential deviations from preferred charging times in [23]. Furthermore, [24] proposes a centralized charging scheme that adjusts charging activities based on battery energy level and kWh rating though V2G operations are again omitted, leaving potential flexibility unexploited. Overall, these works can be grouped into three main categories:

- Cost-focused approaches [20], [21] that optimize economic performance but neglect overload management and bidirectional energy exchange.
- User engagement frameworks [22] that enhance participation but lack technical integration of V2G.
- Overload management strategies [23], [24] that improve grid stability but may compromise user satisfaction and still omit V2G integration.

These limitations reveal a research gap in the absence of a unified approach that simultaneously addresses overload prevention, integrates V2G operations for grid support, and preserves customer satisfaction. This gap presents a significant barrier to achieving both grid stability and user acceptance in large-scale EV adoption.

To address these limitations, this paper proposes a day-ahead EV charging framework for a centralized residential charging facility. The approach combines a valley-filling strategy for off-peak load shifting, a risk threshold mechanism to identify suitable charging slots, and a genetic algorithm (GA)-based optimization process for allocating EVs during V2G discharging operations. A discharge threshold of 30% state of charge (SOC) is applied to protect battery health. The proposed framework ensures effective overload mitigation while respecting user preferences, thereby bridging the gap between technical efficiency and customer-centric service. The main contributions of this work are summarized as follows:

- Proposes a day-ahead centralized EV charging framework for residential charging facilities that integrates overload prevention, V2G operations, and user preference preservation.
- Employs a valley-filling strategy to shift EV charging loads to off-peak hours, flattening the load curve and improving grid efficiency.
- Collects user-preferred charging times and vehicle details to ensure customer satisfaction is maintained alongside technical optimization.
- Utilizes a GA to allocate EVs in overloaded slots during V2G operation, ensuring optimal discharging to mitigate network stress.

The remainder of this paper is organized as follows: section 2 details the proposed methodology, mathematical modelling, and flowchart representation. Section 3 presents simulation results and performance analysis. Section 4 concludes the paper with key findings and future research directions.

2. PROPOSED METHOD

The coordinated charging structure for EVs must implement an efficient charging scheme to address complex challenges including grid stress, user convenience, and limited resources in centralized facilities. A visual representation of this coordinated approach within a centralized charging station is illustrated in Figure 1. The diagram illustrates an EV charging ecosystem. Power from the grid is supplied through a distribution transformer to an EV charging station. The charging station serves both customer-owned EVs and a dedicated EV fleet for V2G operation. An aggregator manages the system, performing tasks such as mathematical modeling, tariff setting, and charging scheme control.

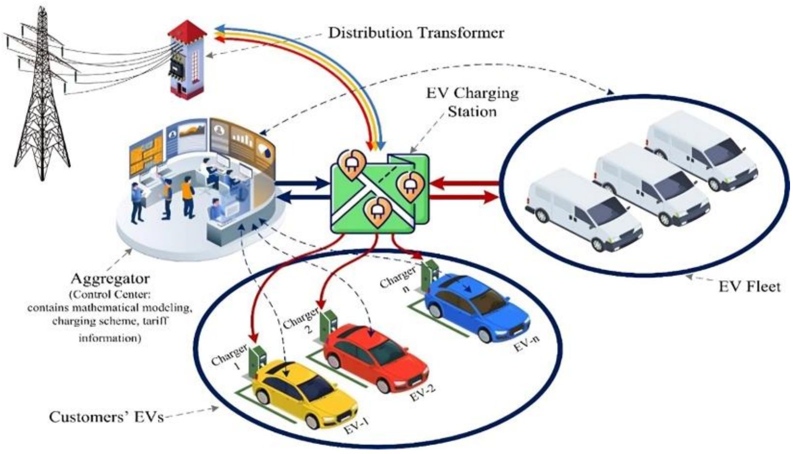

Figure 1. Illustrative overview of the coordinated charging framework in a centralized charging station

The proposed methodology is structured with two consecutive stages. In the beginning, it involves the development of mathematical models and workflow to facilitate parameter computation related to charging slot identification, EV allocation, overload detection, and V2G operation. The second stage represents the deployment of GA for optimal allocation of EVs into the overloaded slots to resolve overloading and ease burden on the transformer.

2.1. Mathematical modelling and workflow

Figure 2 illustrates the flowchart of the proposed day-ahead charging framework implemented at a centralized charging facility. In this approach, it is assumed that the charging station is outfitted with N fast charging ports each having an equivalent power rating. The charging station is designed to accommodate charging for k ∈ {1, 2, 3, …, 50} number of EVs. Additionally, an EV fleet comprising p ∈ {1, 2, 3, …, 10} vehicles is designated to provide additional energy support at the time of overloading. In this research, the entire day is divided into 24 discrete time slots as n ∈ {1, 2, 3, …, 24}, each representing a one-hour interval. The proposed methodology follows a structured process comprising four sequential steps which are described below:

a. Step-1 (charging timeslot identification): in the initial step of the framework, the forecasted day-ahead demand curve is obtained, assuming a reliable and accurate load forecasting technique is already in place to predict the energy demand for the following day. Subsequently, the excess energy for each timeslot is calculated using (1). Once the excess energy in each timeslot is derived, possible timeslots for charging are identified using (2), considering a risk threshold to adopt for any sudden changes in demand pattern [25].

$$P_{excess}^{n} = P_{supply} - P_{demand}^{n} \quad (1)$$

$$t_{charging}^{n} = f(P_{excess}^{n}, thr) \quad (2)$$

where, P_{excess}^{n} represents the excess energy in the 'n-th' slot, P_{supply} denotes the maximum supply capacity of the residential distribution feeder, P_{demand}^{n} indicates the electricity demand in the 'n-th' slot, $t_{charging}^{n}$ represents the available timeslots for EV charging, and thr denotes the risk threshold.

After the identification of charging timeslots, EV users are notified of these slots along with the applicable charging tariff set by the respective regulatory body. Users are then requested to provide their vehicle information and preferred charging timeslot.

b. Step-2 (collection of EV data and allocation): in this step, EV user data including battery capacity, present SOC, required final SOC and timeslot preference is collected. Based on this information, the needed kWh for charging is calculated using (3) [23]. After that, the EVs are allocated to their preferred timeslots and the total needed kWh by the EVs in each identified timeslot is calculated.

$$kWh_{req}^{k} = \frac{SOC_{F}^{k} - SOC_{C}^{k}}{kWh_{rated}^{k}} \quad (3)$$

where, kWh_{req}^{k} represents the required kWh for 'k-th' EV, SOC_{F}^{k} denotes the final required SOC level for 'k-th' EV, SOC_{C}^{k} is the present SOC level of 'k-th' EV, and kWh_{rated}^{k} refers to the kWh rating of 'k-th' EV.

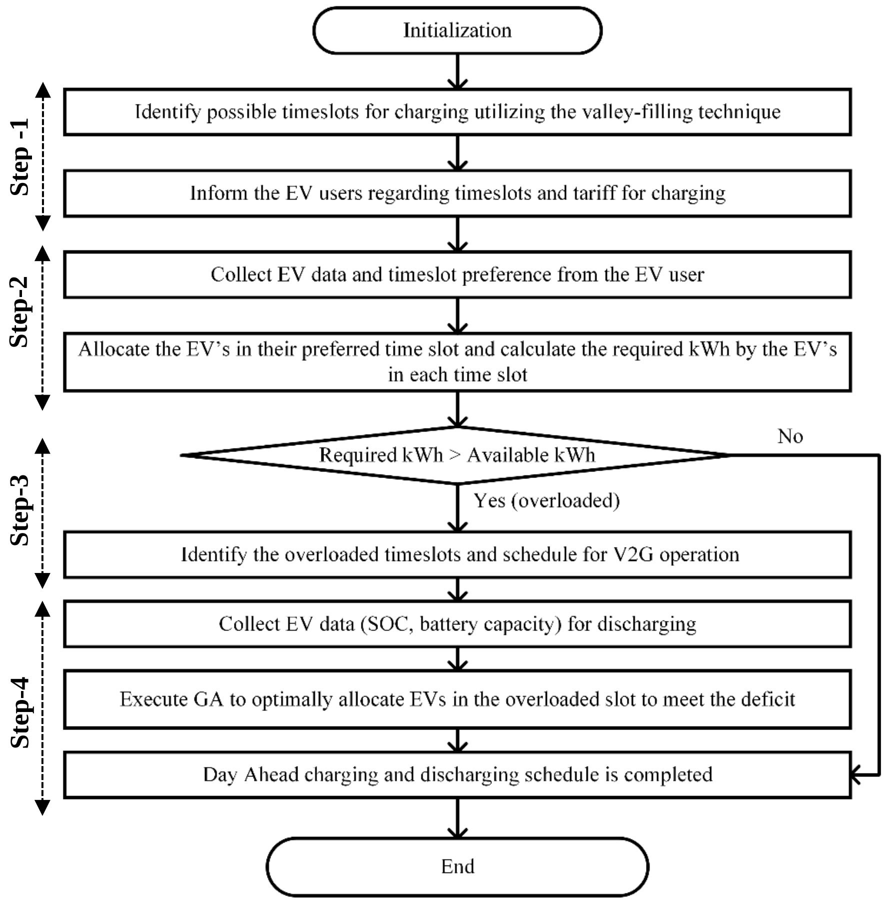

Figure 2. Flowchart of the proposed scheduling framework

c. Step-3 (detection of overloading): in this step, the algorithm evaluates the energy balance in each timeslot to identify any potential case of overloading. A timeslot is considered overloaded if the energy required by the EVs is greater than the available kWh in that slot. If no overloading is found, indicating that all slots have sufficient energy to accommodate the scheduled EVs and the day ahead scheduling is completed. However, if any or multiple slots are found to be overloaded, the algorithm identifies the overloaded timeslots and quantifies the energy shortfall that is, the additional kWh required to meet the demand through V2G operation.
d. Step-4 (additional kWh support through V2G operation): in this step, to address the deficit in overloaded timeslots, V2G operation is enabled. EV users are informed about the overloaded timeslots, and relevant vehicle data such as present SOC and battery capacity are collected. The dischargeable kWh of the EVs is then calculated using (4):

$$kWh_{dis}^{p} = kWh_{rated}^{p} \times SOC_{dis}^{p} \tag{4}$$

where, kWh_{rated}^{p} represents the rated battery capacity of the 'p-th' EV and SOC_{dis}^{p} represents the dischargeable SOC by the 'p-th' EV.

2.2. Optimal allocation of EVs to overloaded timeslots for V2G operation by GA

The optimum allocation of EVs for discharging is determined through GA- based optimization so that there is no loss of energy. GA is a nature inspired metaheuristic optimization technique that mimics the process of natural selection to solve complex optimization problems [26]. In recent years, such algorithms have gained widespread acceptance across various domains related to engineering, politics, management and economics due to their robustness and adaptability [27]. The reason for choosing GA over alternatives like particle swarm optimization (PSO) and mixed-integer linear programming (MILP) is its ability to handle combinatorial assignments through permutation-based evolution where PSO (designed for continuous optimization) and MILP (limited by scalability) often struggle [28]. Additionally, GA offers better computational efficiency for moderate sized problems, making it a practical trade-off between performance and complexity.

The objective function of the GA in the V2G operation is to minimize the total surplus energy (the excess energy after covering the deficit) over all overloaded slots and can be mathematically formulated as (5):

$$min_{p(.)} \sum_{n\in S}[kWh_{dis}^{p(n)} - kWh_{deficit}^{n}] \quad (5)$$

Subject to constraints (6)-(8):

$$p(n) \in \{1, 2, \dots, 10\}; \forall_n \in S \quad (6)$$

$$p(n) \neq p(m); \forall_{n,m} \in S, n \neq m \quad (7)$$

$$kWh_{dis}^{p(n)} \geq kWh_{deficit}^{n}; \forall_n \in S \quad (8)$$

where, $kWh_{dis}^{p(n)}$ is dischargeable kWh of the ‘p-th’ EV assigned to slot n, $kWh_{deficit}^{n}$ is deficit kWh of slot n, S is set of overloaded slots with deficit $D_n > 0$, and m is number of overloaded slots.

The algorithm follows the sequential steps below:

- Initialization of parents and fitness function: the GA starts by gathering data on both the overloaded timeslots and the available EV fleet. For each overloaded slot, the algorithm records the deficit kWh that must be supplied through discharging. For each EV, the algorithm collects the corresponding dischargeable kWh, the amount of energy that can be safely discharged without compromising the vehicle's operation. These values form the foundation of the allocation process. Next, two parent solutions are denoted as $p_{1(n)}$ and $p_{2(n)}$ that are randomly initialized. Each parent is a list of EV identifiers (such as EV 1 and EV 3), with the list length equal to the number of overloaded slots. The parents are generated by randomly selecting n EVs from the full fleet, ensuring that each EV is uniquely assigned and meets the minimum energy requirement for its respective slot. The fitness function is then defined. In this algorithm, the fitness of a solution is measured by how closely the assigned EVs meet (but do not significantly exceed) the energy deficits of the corresponding slots. Solutions where the energy supplied perfectly matches the required deficits with minimal surplus are considered optimal. A secondary constraint is also defined that is no EV may be assigned to more than one slot, and each overloaded slot must be served by exactly one EV.
- Evaluation of fitness and crossover operation: in this phase, the algorithm evaluates the two parent solutions to determine whether either satisfies the termination condition, which involves matching the overloaded slots with energy supply values that meet or slightly exceed the deficits without redundancy. If both parent sets are feasible, the algorithm calculates the total energy surplus of each and retains the one with the minimum surplus. If neither parent set satisfies the constraints, the algorithm initiates a crossover process. A single-point crossover is performed by selecting a random position in the parent lists and exchanging segments of EV identifiers between $p_{1(n)}$ and $p_{2(n)}$ beyond this crossover point. This operation creates new combinations of EV-slot pairings by combining elements from both parents, which may result in improved solutions in subsequent iterations. After crossover, the new parents are checked and corrected to ensure feasibility: duplicated EVs are replaced, and energy constraints are enforced.
- Mutation: following crossover, the algorithm proceeds with a two-stage mutation process to inject diversity into the population and help escape local optima. In the first stage of mutation, a position within each parent list is randomly selected with a probability of 40%. The EV assigned at this position is temporarily removed (set to null or 0), effectively "deleting" it. In the second stage, a new position is again randomly selected based on a 30% probability. The vacant or mutable slot is then filled with a randomly selected EV from the overall pool, ensuring that this EV has not already been assigned and has sufficient disposable energy to serve the new time slot.
- Iterative termination and optimal solution selection: after crossover and mutation, the updated parent sets are re-evaluated. The algorithm checks if either of the parent solutions now satisfies the termination conditions indicating that all slots are covered by unique EVs whose dischargeable energy meets or slightly exceeds the respective deficits. If the condition is met, the iterative loop halts. The final selection of the "best" or near-optimal solution is made using a greedy method: the algorithm compares the total dischargeable energy provided by each parent and selects the one with the smallest surplus over the slot

deficits. This selection ensures minimal waste of energy and efficient use of the EV fleet. The solution is then stored as the finalized allocation strategy for the current overload scenario.

– Termination and output storage: once a valid solution is identified and stored, the algorithm proceeds to terminate. The selected EV to slot mapping is saved for execution or later review, and the process may repeat for other overloaded slots in the broader system, if any exist. By iterating over all such scenarios, the GA ensures that each time slot is optimally supported by discharging EVs in a way that respects energy limitations and maximizes system efficiency.

3. RESULTS AND DISCUSSION

The proposed methodology is implemented and simulated in MATLAB using the optimization and computational toolboxes. A total of 50 EVs are considered for charging, with an additional 10 EVs allocated for V2G operation during periods of overloading. A centralized residential EV charging station is considered where there are three fast chargers each having an identical power rating of 50 kW. Among them, one charger is equipped with bi-directional power transfer capability, allowing only one EV to discharge at any given time slot. Furthermore, a discharge threshold of 30% is considered to prevent battery degradation during V2G operation.

Figure 3 presents the charging slot identification process and the applicable tariff structure for EV charging. Specifically, Figure 3(a) illustrates the forecasted day-ahead demand curve alongside the maximum supply capacity, corresponding to the 180 kW transformer rating of the residential feeder considered in this study [29]. The peak demand occurs between 11:00 PM and 12:00 AM, reaching up to 176 kW. Figure 3(b) shows the excess power available in each timeslot, computed using (1), while Figure 3(c) depicts the identified available timeslots for charging as derived from (2). To mitigate the impact of sudden load fluctuations, a risk threshold of 15% of the maximum supply capacity equal to 27 kW is applied. Based on this threshold, charging is permitted from 12:00 AM to 6:00 PM, whereas the remaining slots are restricted due to insufficient excess power. Finally, Figure 3(d) presents the time-of-use charging tariff for the MT-11 kV line as set by the Bangladesh energy regulatory commission (BERC) [30].

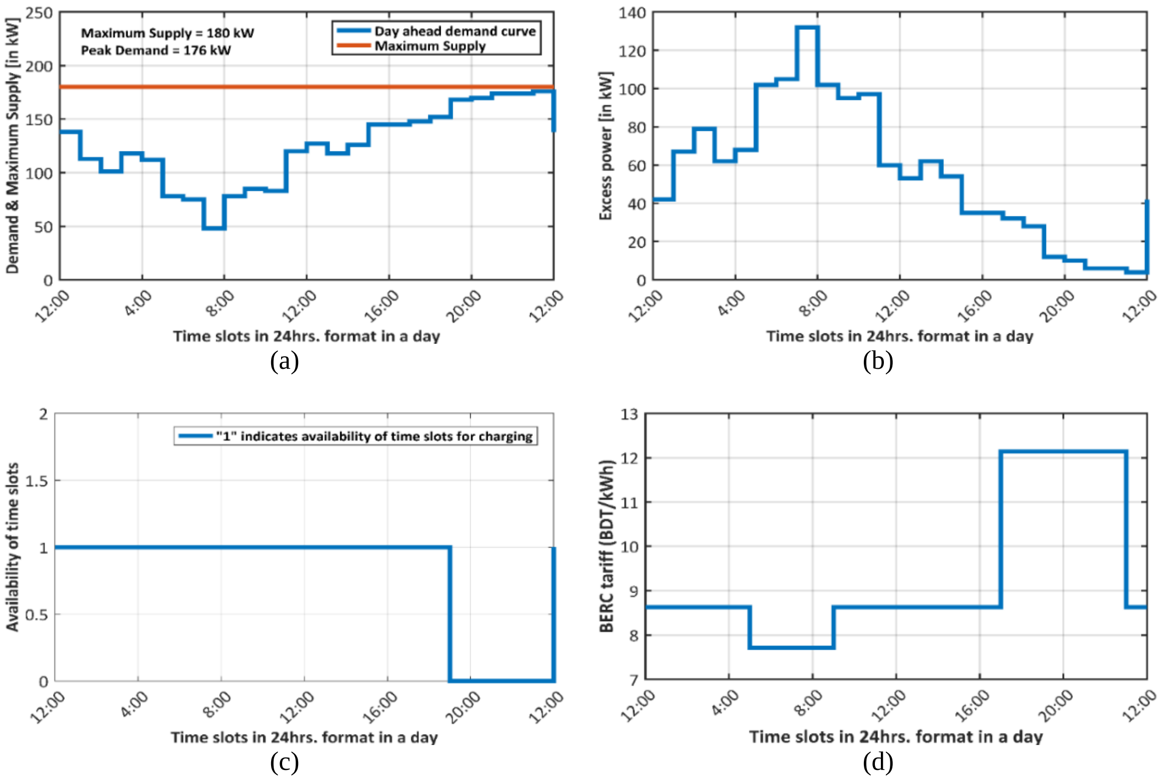

Figure 3. Charging slot identification and applicable tariff for charging; (a) day-ahead demand curve with maximum supply capacity, (b) excess power in each timeslot of the day, (c) identified timeslots for charging, and (d) applicable BERC tariff in BDT per kWh for charging

Figure 4 illustrates the detection of overloading in the identified charging timeslots. Once the charging timeslots are identified, the EV users are notified of the available slots along with the applicable charging tariff. Subsequently, user-specific data including battery capacity, present SOC, required final SOC and timeslot preference is collected. Based on these preferences, EVs are initially allocated to their preferred timeslot and the total energy required by the EVs are calculated to identify any potential case of overloading as illustrated in Figure 4(a). Figure 4(b) depicts the overloading scenario of the timeslots where the 7th timeslot (6:00 AM-7:00 AM), 10th timeslot (9:00 AM-10:00 AM) and 15th timeslot (2:00 PM-3:00 PM) are identified as overloaded by the algorithm.

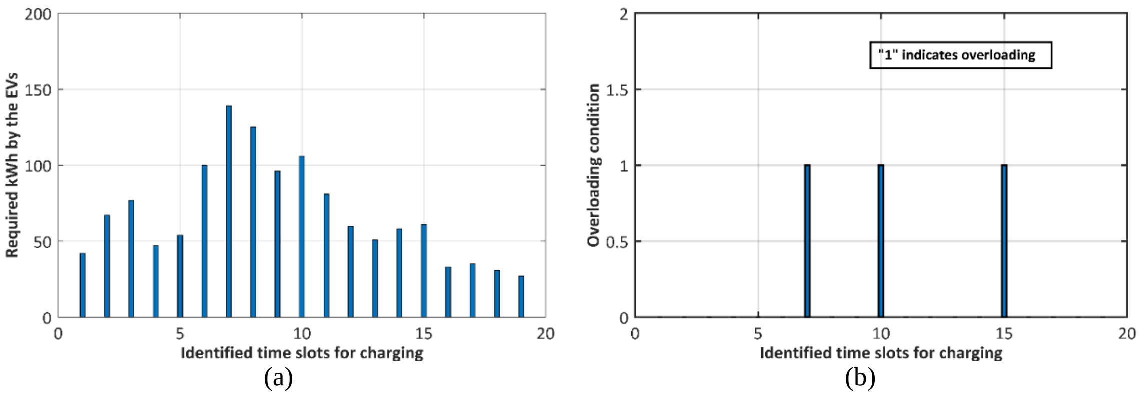

Figure 4. Detection of overloading; (a) total required kWh by the EVs in each identified timeslot for charging and (b) overloaded scenario of the timeslots after the allocation of EVs

The methodology then schedules for the V2G operation to compensate for the deficit in the overloaded slots. The whole V2G operation process in illustrated in Figure 5. During this process, the users in the EV fleet are informed about the schedule for discharging. The users in return provide information about their battery capacity and present SOC from which the dischargeable kWh by the EVs is calculated using (4) as shown in Figure 5(a). This information is then utilized by the GA for optimal allocation of EVs in the overloaded slots to meet the identified deficit. Figure 5(b) indicates the identified EV data with required kWh by the GA for V2G operation. In this case, allocation of EV5 in the 7th slot resolves the overloading by providing additional kWh support to meet the deficit. The same optimization algorithm is subsequently applied to the 10th and 15th time slot where similar overloaded conditions are observed. The GA identifies EV2 and EV8 as the optimal candidates for discharging in the 10th and 15th timeslots, respectively. Figures 5(c) and (d) indicates these optimal allocations and corresponding energy contributions by GA for resolving the overloading scenarios.

The execution of the V2G operation successfully resolves the overloading in the 7th, 10th, and 15th timeslot. This outcome demonstrates that the support provided by the optimally allocated EVs through controlled discharging has effectively mitigated the energy deficits in the overloaded slots. As a result, the network is stabilized, and the charging demand is redistributed within the operational and thermal limits of the distribution system. With the overloaded condition addressed, the day-ahead charging schedule is now considered as completed and the EV users are informed about their corresponding charging and discharging timeslot in accordance with the optimized allocation strategy. Figure 6 compares the demand curve before and after EV integration. A noticeably flatter profile with a more uniform distribution of the demand across the timeslots is obtained after EV integration. The load factor defined as the ratio of average to peak demand is significantly improved from 70.68% to 82.24%. This enhancement directly results from the optimal allocation of charging and discharging activities indicating better utilization of the available energy resources and underscores the effectiveness of smart charging coordination. A higher load factor enables utilities to defer or avoid costly investments in transformer, feeders and generation capacity, while consumers are benefitted from cheaper charging rates by shifting demand to off-peak periods. Besides, since no users are rejected or deferred from charging, the customer satisfaction index remains at 100% which is a key objective of this research. Moreover, users participating in the V2G operation can obtain financial incentives, provided a well-structured discharging tariff is implemented that incorporates dynamic pricing, compensation for battery degradation and differentiates value on grid services.

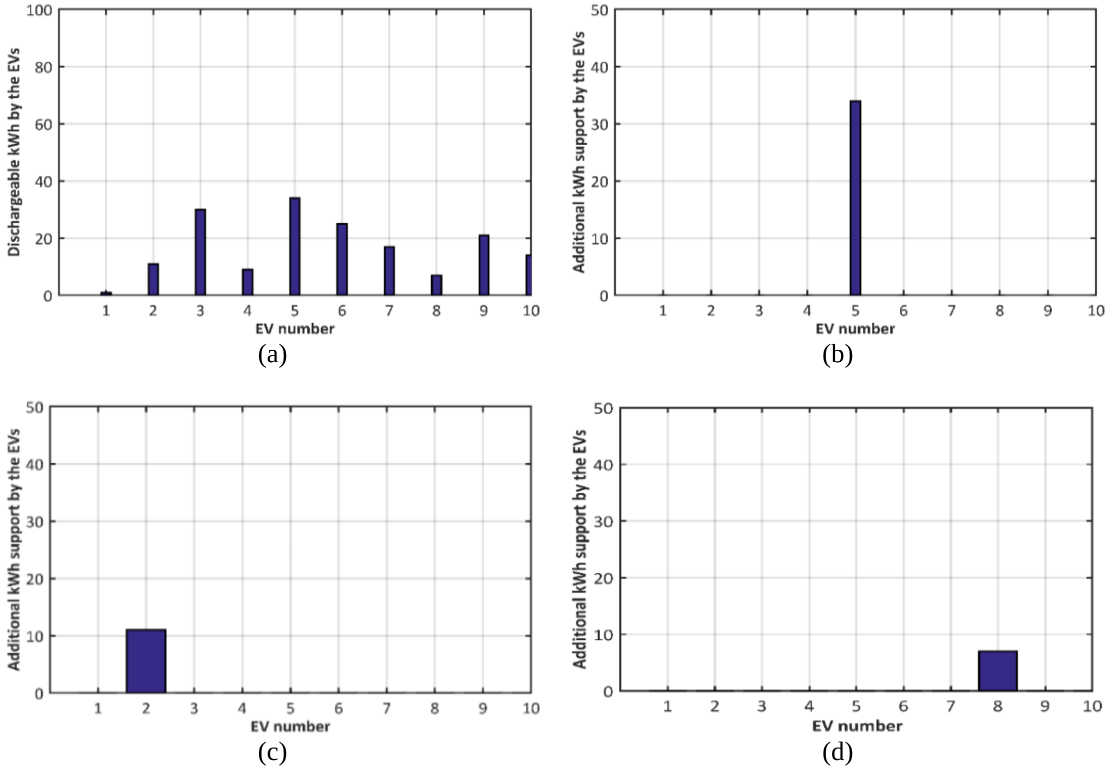

Figure 5. V2G operation to meet the deficit in overloaded slots; (a) calculated dischargeable kWh by the EVs in the fleet, (b) additional kWh support to the 7th slot by EV5, (c) additional kWh support to the 10th slot by EV2, and (d) additional kWh support to the 15th slot by EV8

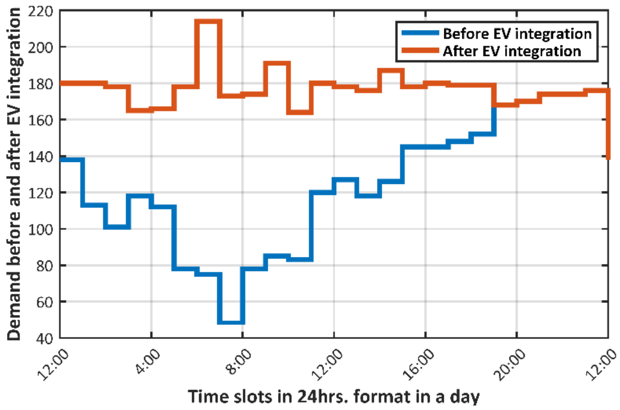

Figure 6. Demand curve before and after EV integration

To evaluate the robustness of the proposed charging scheme, a sensitivity analysis is performed by varying the risk threshold by ±5% from its base value. A 5% increase in the risk threshold reduces the number of available charging slots by 21%, leading to higher occurrence of overloaded slots and requiring more EVs to participate in the V2G operation to meet the deficit. Conversely, a 5% decrease in the risk threshold increases the number of available charging timeslots by 10%, thereby reducing the frequency of overloaded slots and lowering the V2G participation requirement. This analysis demonstrates the effectiveness of the proposed charging scheme under varying operational constraints while highlighting the trade-off between charging slot availability and V2G demand.

Overall, this coordinated approach presents a valuable contribution by addressing network stress and customer satisfaction simultaneously, which are gaps that have remained largely unaddressed in prior literature. The proposed framework can be scaled for larger EV fleets or multiple charging stations via fleet aggregation and adaptive tariff mechanisms. However, implementation of this framework into the existing system entails certain constraints. The frameworks deployment depends on the development of a robust, secure and low latency communication infrastructure capable of enabling bi-directional data exchange between EV users and grid operators. Additionally, the charging stations need to be equipped with bi-directional power transfer capability to physically support V2G operations, which may require substantial investment and regulatory alignment. These infrastructural and technological prerequisites represent critical areas for future work, including the exploration of cost-effective communication protocols, interoperability standards, and phased hardware upgrades to facilitate broader adoption. From a modeling perspective, the study assumes accurate load forecasting, a fixed TOU tariff structure that does not account for dynamic pricing variations, and a fixed SOC threshold for charging slot identification, factors that may influence real-world performance. Addressing these infrastructural, technological, and modeling constraints in future work through advanced forecasting methods, adaptive pricing schemes, flexible SOC thresholds, and cost-effective communication and hardware solutions will further enhance the practicality and robustness of the proposed framework.

4. CONCLUSION

This study introduces a comprehensive day-ahead EV charging framework that provides a scalable and user-friendly solution for EV charging coordination, effectively balancing grid stability with consumer autonomy. Simulation results verify its capability to mitigate network stress while ensuring user convenience, achieving an 11% improvement in load factor and thereby enhancing the utilization of available energy resources. From the utility perspective, this improvement can yield both technical and economic benefits by deferring costly infrastructure upgrades, such as transformer or generator replacements. For the EV users, the valley-filling strategy enables access to lower charging tariffs by shifting demand to off-peak periods. Furthermore, users participating in V2G operations can obtain additional tariff incentives provided that a well-designed pricing framework is implemented. By aligning grid stress management with enhanced customer satisfaction, a dimension often overlooked in prior studies, the proposed framework delivers a balanced benefit to both stakeholders. Future work may focus on real time adaptive scheduling, integration with renewable generation forecasts and block chain-based user participation incentives.

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AUTHOR CONTRIBUTIONS STATEMENT

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Tareq Aziz	✓	✓			✓	✓			✓	✓	✓	✓		

C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

Authors state no conflict of interest.

DATA AVAILABILITY

Data availability is not applicable to this paper as no new data were created or analyzed in this study.

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