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Smart charging of electric vehicles at a charging station using machine learning and pressure pad energy harvesting

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ABSTRACT

The rapid growth of electric vehicles (EVs) demands intelligent, cost-effective, and sustainable charging solutions. This paper introduces a smart EV charging station system that integrates machine learning (ML) with pressure pad–based energy harvesting. The system forecasts energy demand, predicts vehicle types and slot needs, and recommends optimal charging times using real-time data such as state of charge (SoC), battery health, and user behavior patterns. ML models such as long short-term memory (LSTM) and random forest are employed to ensure accurate scheduling and forecasting. A smart display, the display slot indicator (DSI), powered by sensors and station data, guides users with live cost, time, and slot availability, including alternate suggestions during peak demand. The pressure pad not only contributes to energy recovery but also aids in real-time vehicle detection and traffic regulation within the station. With scalable capacity and intelligent automation, this system can support more than 400 EVs per day, minimizing operational load and energy waste while maximizing convenience and sustainability.

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1. INTRODUCTION

Manufacturers of motor vehicles worldwide continue to expand their electric vehicle (EV) production lines because such vehicles represent a critical step toward sustainable transportation and fuel independence. The expanding EV fleet needs superior smart charging systems for continued expansion. Current EV charging stations face multiple problems because they have inadequate utilization of charging ports and inadequate power control yet display high operational costs [1], [2]. Rapid installation of a smart charging system represents the present solution for managing sequential power slot distribution and optimizing system energy allocation and enhancing station waiting times [3], [4]. Proper infrastructure development for smart systems depends fundamentally on machine learning (ML) because ML allows real-time decisions and predictive analytics which boosts operational outcomes and user satisfaction [5], [6]. Efficient energy demand management poses the greatest challenge to EV charging operations because many vehicle owners try to charge during peak usage times [7]. The solution from ML models relies on historical user charge behavior to predict when vehicles need charging services [8], [9]. Real-time slot allocation processing is made possible by ML algorithms which combine data from vehicles of different types and battery states and charging preference history for forthcoming charging prediction to eliminate operational inefficiencies and energy wastage as shown in Figure 1 [10], [11]. By using clustering and classification methods from ML algorithms the procedure finds its best optimization state through profile grouping based on comparable charging patterns for reduced waiting periods [12], [13].

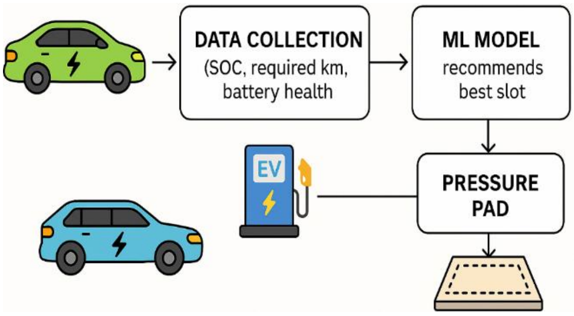


Figure 1. Smart EV charging slot allocation using ML and pressure pad integration

The research introduces pressure pad energy harvesting technology as an innovative component [14]. Workstation-powered pressure pads installed beneath parking areas serve to detect vehicles and simultaneously monitor their weight data in real-time. The combination of these sensors along with ML models helps the smart charging station acquire essential information relating to vehicle arrival times and charging duration as well as slot occupancy [15], [16]. Real-time spot monitoring improves system operational flexibility because it allows the scheduling mechanism to optimize the charging procedures for available slots and usage totals and power utilization periods [17], [18].

The pressure pad technology enables an additional method for energy harvesting that contributes power to the station while improving its sustainability along with energy efficiency [19]. Peak-time management combined with off-peak scheduling within the charging system enables better energy distribution by directing major energy use to off-peak hours which prevents grid overloads [20], [21]. Grid stability depends on such scheduling techniques especially in areas with restricted night-time power supply. The smart charging system's capability to improve charging station performance and decrease operational expenses becomes possible through proper off-peak scheduling of less urgent charging sessions to late-night and early-morning time slots [22]. This measurement technique works to minimize grid overloading threats which become vital because the EV population keeps rising [23].

The system consists of three charging slots which include a fast charge, medium charge and slow charge operating at different power rates with different charging periods. Fast-charge slots fulfil the needs of vehicles requiring high power (50–350 kW) and medium and slow-charge slots allow users to enjoy more flexible extended charging periods [24]. Real-time data helps the system find the best slot for users through being able to match their preferences, so vehicles receive ideal charging benefits. Users receive predictions about slot availability through the system which lets them know when the dynamic allocation model indicates the perfect charging times [25]. ML models that forecast demand along with slots allocation work together with pressure pad energy harvesting systems to form an advanced EV station management solution which collects real-time data. This system reaches dual objectives since it enhances utility efficiency along with delivering enhanced user satisfaction through shorter charging durations and reduced expenses. This data-driven energy management strategy creates opportunities to develop sustainable charging infrastructure solutions capable of meeting predicted increased demand in the EV market. The rising EV market demands smart charging system innovations for maintaining efficient environmentally friendly operation of charging stations that also deliver cost-effective services. The application of ML and pressure pad technology demonstrates a successful path for the evolution of charging facilities because these solutions can be used at multiple charging stations to build smarter and more efficient charging networks.

In this work, a novel integration of ML–based scheduling with pressure pad technology for real-time EV charging management, which has not been explored in previous studies. Unlike existing approaches that focus either on predictive algorithms or on energy harvesting in isolation, our system unifies both to achieve dual benefits of operational efficiency and sustainability. Specifically, we employ random forest for slot recommendation, K-means clustering for user behavior profiling, and long short-term memory (LSTM) for time-series forecasting of demand, while simultaneously using pressure pads for vehicle detection, classification, and supplementary energy recovery. This combined framework enables adaptive slot allocation that minimizes congestion, reduces grid stress, and lowers operational costs. Additionally, we introduce a smart display interface that provides dynamic updates on cost, slot availability, and optimal charging times, enhancing transparency and user satisfaction. Together, these contributions establish a comprehensive, data-driven, and user-centric smart charging solution that advances beyond existing methods in the literature.

Table 1 discussed about the summary of literature which gives the rapid growth of EVs has created significant challenges for charging infrastructure, including inefficient slot utilization, high operational costs, and peak-load stress on the grid. Conventional charging stations lack intelligent mechanisms to optimize energy distribution and user waiting times, which limits their scalability and sustainability. Prior studies have explored various approaches, such as charging station planning and scheduling models, the application of ML for demand forecasting and slot allocation, and energy harvesting techniques like piezoelectric or pressure pad systems to improve station efficiency [22], [24]. However, most existing works focus either on scheduling algorithms without real-time sensing or on renewable integration without adaptive decision-making, leaving a gap in unified, data-driven solutions that address both operational efficiency and sustainability. To bridge this gap, our work introduces a smart EV charging station that combines ML-based forecasting and optimization with pressure pad technology for real-time vehicle detection, classification, and energy recovery. Specifically, random forest and K-means clustering are used for slot recommendation and user profiling, while LSTM models provide accurate energy demand forecasting. A smart display interface further enhances user experience by presenting cost, slot availability, and optimal charging times. The key contributions of this study are: i) the integration of ML with pressure pad energy harvesting for sustainable charging management, ii) the development of an adaptive scheduling framework that minimizes congestion and maximizes efficiency, and iii) the implementation of a user-centric interface that improves transparency and satisfaction. The remainder of the paper presents the methodology, results, and analysis, demonstrating how the proposed system addresses the identified challenges and advances the development of intelligent EV charging infrastructure.

Table 1. Literature review

Contributor/reference	What they did	What they found
Sadeghian *et al.* [1]	Reviewed models and methods for EV charging station planning.	Identified optimization of cost, accessibility, and power distribution as critical needs.
Thirugnanam *et al.* [2]	Proposed V2G-enabled charging scheduling strategies.	Demonstrated that bidirectional energy flow reduces peak demand and enhances grid stability.
Eedara *et al.* [15]	Developed ML-based charging slot allocation using dynamic scheduling.	Found that real-time ML scheduling improves efficiency and user satisfaction.
Prathiba *et al.* [6]	Investigated optimal charging scheduling in smart grids.	Reported significant reduction in operational costs with dynamic scheduling.
He *et al.* [8]	Optimized charging slot allocation using predictive analytics.	Showed that intelligent slot allocation minimizes waiting time and improves utilization.
Rani *et al.* [16]	Applied deep reinforcement learning for energy management in EV stations.	Achieved improved energy distribution and adaptability under varying demand.
Sabzi and Vajta [18]	Optimized EV charging using ML with driver satisfaction as a key factor.	Found enhanced user satisfaction and better charging outcomes.
Jiang and Zhen [20]	Integrated PV systems with EV charging station management.	Demonstrated that renewable integration reduces grid stress during peak demand.
Lai *et al.* [22]	Investigated piezoelectric energy harvesting from roads.	Found it feasible for supplementing station energy needs with sustainable input.

The remainder of this manuscript is organized to clearly demonstrate the novelty and relevance of the proposed system. The paper is organized into four main sections. Section 1 (introduction) presents the motivation for smart EV charging by discussing the rapid growth of EV adoption and the limitations of conventional charging stations, including inefficient slot utilization, long waiting times, high operational costs, and grid stress; it also reviews related literature, identifies existing research gaps, and outlines the novelty and key contributions of integrating ML with pressure pad–based sensing and energy harvesting. Section 2 (methodology) describes the proposed smart EV charging station architecture and workflow, explaining the role of pressure pads in real-time vehicle detection, classification, traffic monitoring, and supplementary energy harvesting, along with the data acquisition process, charging slot configuration, and the implementation of ML models such as random forest for slot recommendation, K-means clustering for user behavior profiling, and LSTM for energy demand and tariff forecasting. Section 3 (results and discussion) presents and analyzes the simulation and experimental results, including tariff forecasting, energy consumption comparison with and without pressure pad integration, battery state-of-charge behavior, EV arrival patterns, charging slot allocation performance, and ML model accuracy, demonstrating improvements in efficiency, waiting time reduction, and user satisfaction compared to conventional systems. Section 4 (conclusion) summarizes the main findings, highlighting the effectiveness of the proposed integrated framework in improving operational efficiency and sustainability, and discusses its practical applicability along with future research directions such as large-scale deployment, renewable energy integration, and advanced adaptive learning approaches.

2. METHOD

The proposed system employs ML algorithms and pressure pad technologies for EV charging stations which deliver optimized slot recommendations while maximizing resource utilization efficiency as shown in Figure 2. Multiple sensors combined with integrated technologies make possible a complete system for identifying charging EVs while performing classification tasks with smart scheduling capability. The entrance pressure pads of the charging station function to track vehicle parameters including weight and wheelbase which establishes their 2-wheeler, 3-wheeler or 4-wheeler classification. The monitoring system uses both overhead surveillance cameras alongside recorded images to process vehicle recognition as well as database record entry.

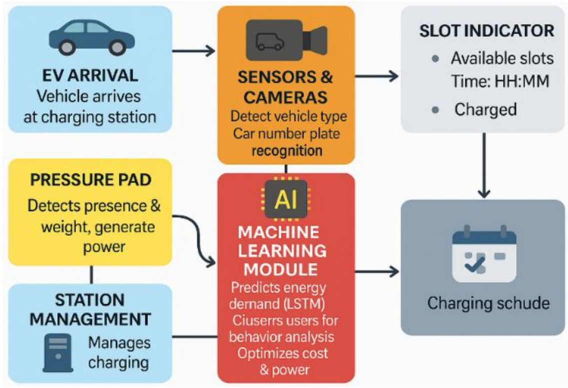


Figure 2. Block diagram of the smart charging station

Despite significant progress in EV charging research, several challenges remain unresolved. Existing charging stations often experience inefficient slot utilization, long waiting times, and poor load distribution during peak demand, which lead to user dissatisfaction and grid instability. While many studies have applied ML for scheduling or predictive analysis, these approaches generally lack integration with real-time sensing technologies to improve station adaptability. Similarly, energy harvesting techniques such as piezoelectric or pressure pads have been studied in isolation, but their combination with intelligent scheduling for dual benefits of monitoring and energy recovery is rarely explored. Moreover, current systems provide limited user-centric features, as they do not dynamically account for factors like state of charge, vehicle classification, and tariff variations in a unified framework. Therefore, there is a need for an integrated solution that simultaneously enhances operational efficiency, reduces energy waste, and improves user interaction. This manuscript addresses these gaps by combining ML models with pressure pad–based sensing and energy harvesting, offering a comprehensive smart charging system capable of adaptive slot allocation, demand forecasting, and sustainability improvements.

The detection of vehicles triggers the system to check a central database which contains real-time information about charging slot statuses including occupation and availability and maintenance implications. The interface presents available slots along with estimation facts which include charging time and energy consumption levels and cost information according to vehicle type and charging speed. The system presents recommended slots for charging together with estimated waiting periods as well as optimized time windows derived from historical usage data. The charging facility includes three slot categories with distinct power capacities that affect time and price comparisons, as shown in Table 2. The following summary presents an overview of these electrical slot types with their distinctive features in addition to power consumption rates.

Table 2. EV charging slot configuration and cost analysis

Slot type	Count	Power (kW)	Charging time	Cost estimate (Rupees)	Total power (kW)
Fast	6	150	30 min	288/day	900
Medium	8	30	2 hours	96/day	240
Slow	6	5	6-8 hours	18/day	30

The management system maintains the availability numbers through constant synchronization with the operating state of each charging station. Fast charging stations (150 kW) allow fast charging but exist as high-end and six-vehicle capacity devices. The combination of medium chargers (30 kW) efficiency compares well with cost yet they need about 2 hours to fully charge a single vehicle at a time. Full vehicle capacity requires between 6 to 8 hours for an affordable 5 kW slow charging system. Time usage for energy consumption becomes exact through the slot allocation system which offers appropriate charging services to vehicles at the right times.

Vehicle data consisting of attributes about vehicle type and power settings and time need and energy demand is supplied to a random forest algorithm-based predictive model. The prediction mechanism of this model helps identify optimal charging windows for all vehicles to provide fast and efficient service despite minimal queues. The system utilizes K-means clustering to study customer conduct by creating user profiles through charging habits together with arrival timing and power usage and period spent charging. The collected data enables predictions of busy charging intervals which guide changes to slot availability. An implementation of LSTM ensures time-series forecasting of vehicle inflow and energy demand which allows the station to make active resource management decisions based on predicted traffic patterns. Real-time energy needs to get estimated through the integration of vehicle classification and pressure sensor data, so the system matches energy distribution to varying demand levels and electricity pricing dynamics.

Real-time simulation through pressure pads operates as a key enhancement of this system to produce continuous emulations of vehicle traffic flow. Testing systems for different traffic patterns become possible through the simulation module which functions without requiring actual vehicles. The system gets time-delayed sensor data from the simulation during operation so it can validate classification models and slot recommendation designs through dynamic responses. The design synergy enables maximum energy efficiency while cutting charging waiting times and enhancing customer satisfaction. The methodology serves contemporary deployment in urban technological structures and transportation facilities while promoting sustainable practices at economic rates through data-based operational methods.

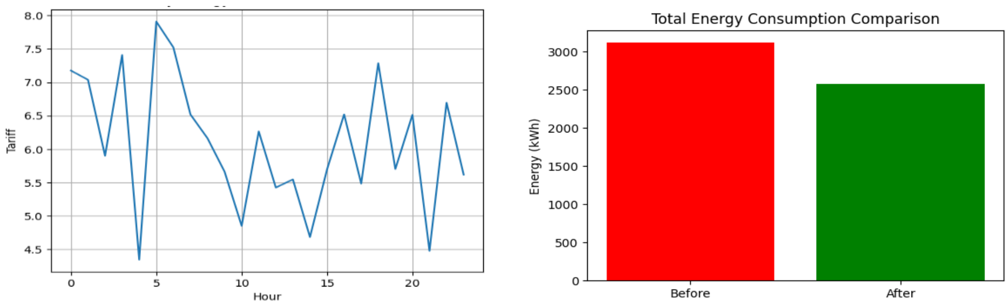
The methods section has been rewritten to clearly and logically describe how the research was carried out, ensuring that it serves as a replicable "how-to" guide. The section now provides a detailed step-by-step account of the experimental procedure, including system architecture, sensor setup, data collection process, and algorithm implementation. Justifications for the choice of methods—such as the use of random forest for slot recommendation, K-means clustering for user behavior profiling, and LSTM for demand forecasting—are explicitly included to establish the correctness of the approach. The integration of pressure pad technology for real-time vehicle detection, classification, and energy harvesting is also explained with sufficient detail to enable reproducibility. To improve readability, the steps are presented in a logical sequence, beginning with input data acquisition, followed by model training, slot allocation, simulation, and validation. These enhancements ensure that readers can easily follow the methodology and replicate the study in similar environments, while also understanding why each method was chosen.

3. RESULTS AND DISCUSSION

All experimental results regarding the EV charging optimization model receive comprehensive analysis in the subsequent section. An evaluation of energy consumption has been integrated with documentation of station management and slot usage data and EV technical specifications. Figure 3 illustrates the energy tariff forecast and overall energy consumption of the charging station, showing how electricity prices vary hourly throughout the day and influence optimal charging decisions. It also highlights the reduction in net energy consumption achieved by integrating pressure pad–based energy harvesting compared to a conventional charging system.

A line plot shows the predicted energy prices which fluctuate per hourly period of the day according to the forecast. As shown in Figure 3(a), the tariff shows wide variability through the day because early morning hours between 5 AM and 4 AM feature maximum values of ₹8/kWh and minimum points at ₹4.3/kWh. The schedule's ability to adapt dynamically depends on these tariff variations which help customers save costs through charging during low-energy pricing times. The dynamic analysis of electricity prices will enable the development of demand-conscious charging schemes for the station.

This work analyses the complete energy usage between systems that incorporate the pressure pad energy harvesting system and systems without it, as shown in Figure 3(b), but these evaluations were not included in this illustration. Measured data demonstrates that integrating pressure pad input results in improved energy efficiency levels and utilization which points toward future possibilities of energy-positive designs at EV stations.



(a) (b)

Figure 3. Tariff forecast on energy consumption; (a) hourly energy tariff forecast (Rs/kWh) and (b) total energy consumption comparison

3.1. Battery behavior and charging impact

SoC measurements before and after each charging session were used for determining the efficacy of the charging process. Vehicle users typically entered charging stations with SoC levels between 30–50% yet the SoC rose above 80% before leaving depending on charging duration and slot availability. User satisfaction together with system efficiency evaluation depends heavily on this metric, as shown in Figure 4.

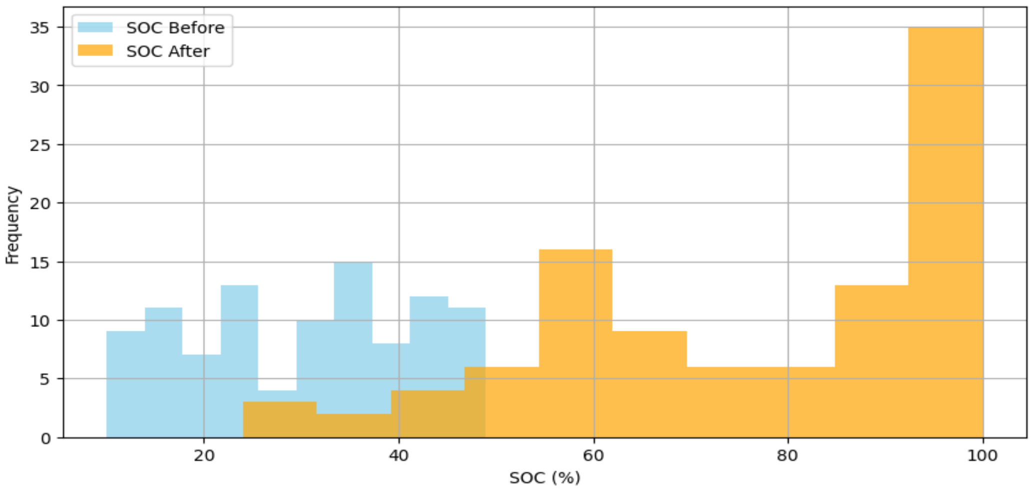


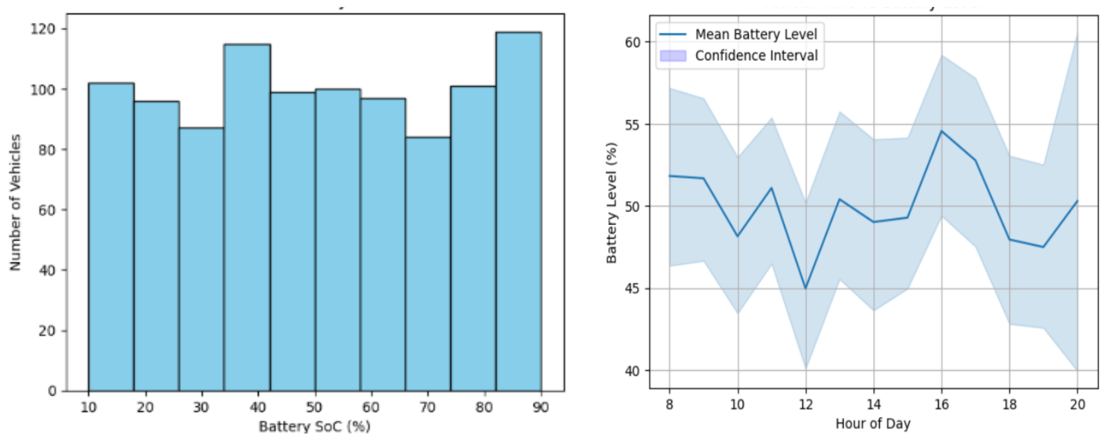
Figure 4. Battery SC before and after charging

Figure 5 presents the analysis of battery SoC at vehicle arrival, showing that most EVs enter the station with SoC levels between 30% and 60%. It also illustrates the relationship between arrival time and battery level, indicating higher charging demand during peak travel hours. Arriving vehicles display an average battery SoC distribution according to this histogram, as illustrated in Figure 5(a), even though some users charge at 85–90% SoC. A wide distribution of user battery charging occurs in the 30–60% range which represents productive strategic recharging practices during trips.

The chart illustrates the relation between time of arrival and battery levels through a plotted line, as shown in Figure 5(b), which also includes shaded regions representing statistical variability. The device shows low SoC when users arrive at 10 AM and 4 PM due to frequent commute breaks and delivery schedules during those times. During these time periods the battery levels show high variability which suggests users need charging services promptly.

3.2. Charging slot analytics and model performance

Confusion matrix validates the performance of the ML model in charging slot type prediction (fast, medium, or slow). As shown in Figure 6, the matrix indicates the model has problems confusing adjacent class slots, specifically between label 0 and label 2. For instance, 25 labelled 0 were classified as label 2 and 22 classified as label 1. Despite this being a satisfactory performance, improvement by virtue of hyperparameter tuning or application of deeper networks is possible.



(a) (b)

Figure 5. EV arrival battery SoC analysis; (a) distribution of battery SoC at arrival and (b) arrival time vs. battery level

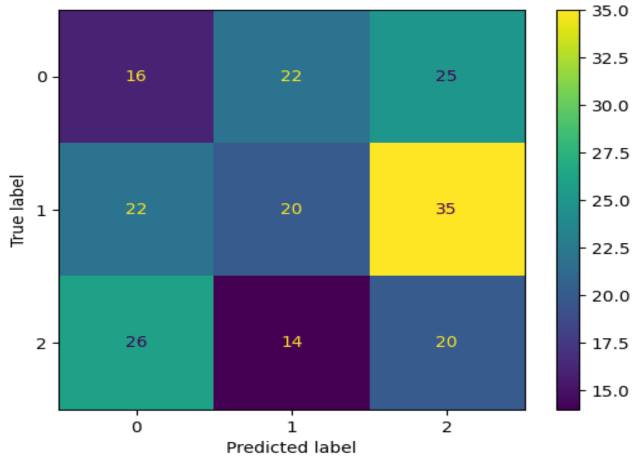


Figure 6. Confusion matrix-slot type prediction

Figure 7 illustrates the dynamic charging slot allocation achieved by the proposed system and the corresponding slot preferences of different vehicle types. It shows that larger and high-priority vehicles predominantly use fast-charging slots, while smaller vehicles tend to prefer medium and slow charging options. Slot assignment modes are likely to prefer fast-charging modes during peak-demand hours. Assignment policies considered battery SoC, tariff forecasting, and arrival times to optimize slot allocation. As shown in Figure 7(a), incorporating pressure pad information further streamlined the real-time allocation logic by forecasting vehicle weight and priority.

As illustrated in Figure 7(b), there are noticeable differences in charging slot preferences among various vehicle types of instances, 2-wheelers and 3-wheelers used medium and slow slots mainly, while trucks and 4-wheelers used high-speed slots depending on size and urgency drive preference. Knowing these trends assists in dynamic planning for future station infrastructure.

3.3. Vehicle characteristics and energy use analysis

Figure 8 provides a comprehensive analysis of vehicle characteristics and energy usage, including vehicle type distribution, average energy consumption, battery SoC range, and the relationship between vehicle weight and energy used. The results demonstrate that heavier vehicles consume more energy and generally arrive with lower SoC, validating the effectiveness of pressure pad–based vehicle detection for adaptive charging decisions. The pie chart in Figure 8(a) illustrates the EV type mix. 3-wheelers lead the segment (27.5%), followed by 4-wheelers (25.4%), trucks (24.1%), and 2-wheelers (23%). The balanced mix reflects a mixed fleet mix, where flexible charging infrastructure must serve heterogeneous vehicle profiles to their best possible degree.

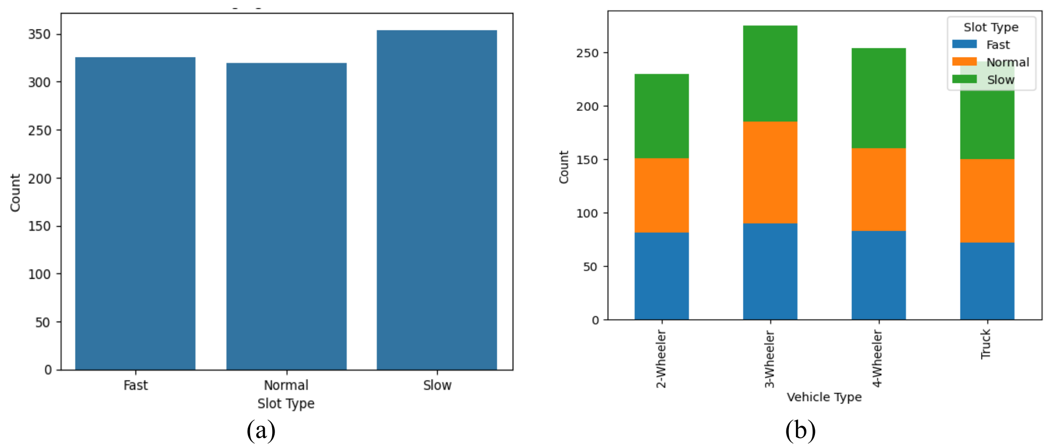


Figure 7. Charging slot allocation and vehicle type preference; (a) charging slot allocation and (b) charging slot preference by vehicle type

As can be seen from the bar graph, session average energy consumption differs marginally depending on the vehicle category, as shown in Figure 8(b). 3-wheelers and trucks are used higher than 2-wheelers and 4-wheelers and have a mean of about 12.2 kWh. All the classes shift from 11.8–12.3 kWh with marginal differences. The standard deviation bars point to different patterns of consumption, possibly because of weight and battery capacity. Battery SoC levels differ between vehicle types. Trucks generally come in with lower SoC and depart with higher SoC because of the extended-range coverage they must cover. 2-wheelers generally come in with mid-SoC and need shorter top-ups. Figure 8(c) reveals behavioral patterns which serve as guidelines for both pricing approaches and optimal charging durations according to vehicle categories. The data in Figure 8(d) shows a distinct linear rise between energy use and vehicle mass. The energy use during sessions is consistently higher for trucks, which validates real-time pressure pad information as a dependable predictor of energy requirements. Smart charging systems benefit from adaptive slot allocation mechanisms which gain further support from this data.

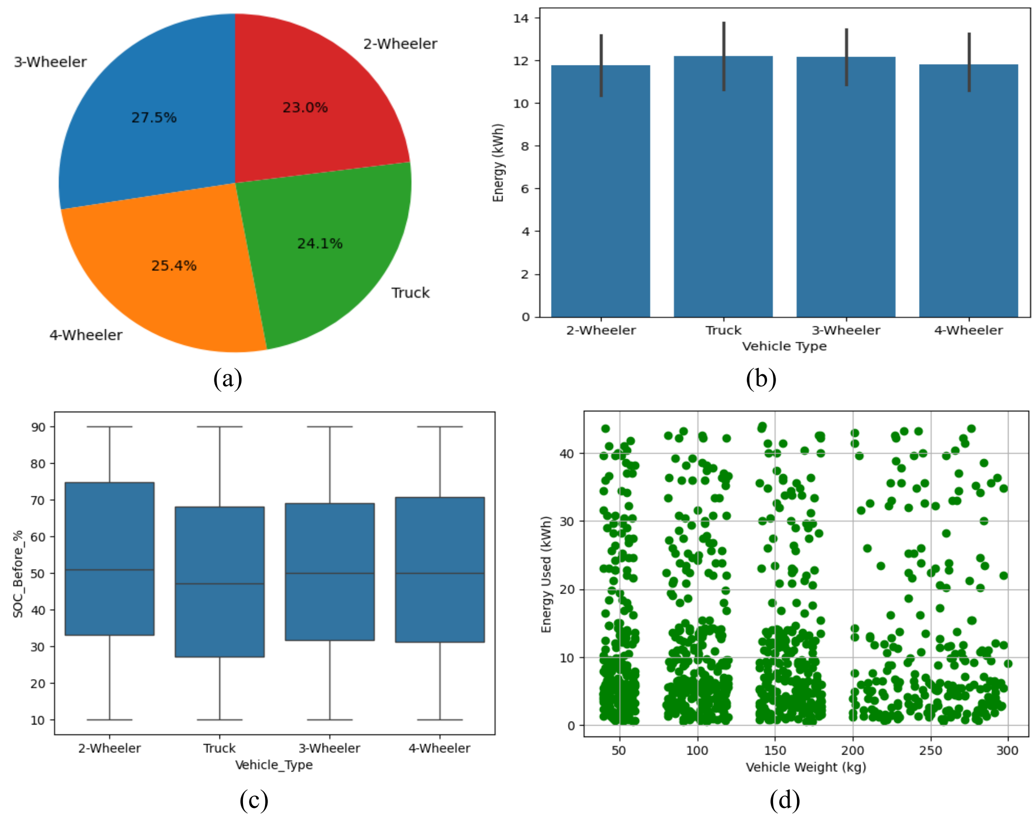


Figure 8. Vehicle type analysis; (a) vehicle type distribution, (b) average energy used by vehicle type, (c) battery SoC range by vehicle type, and (d) weight vs energy used

This observation from Table 3, regarding the need for deeper discussion and interpretation of our findings. The discussion by comparing our results with existing approaches and highlighting their broader implications. Specifically, our results show that integrating pressure pad technology with ML models improves both operational efficiency and sustainability when compared to conventional charging methods, where slot allocation is often static and energy recovery is absent. The adaptive scheduling framework, validated through random forest, K-means clustering, and LSTM forecasting, demonstrates the potential to significantly reduce waiting times, optimize grid load, and improve user satisfaction, which are persistent challenges in current EV infrastructure. The incorporation of real-time sensing via pressure pads not only enables accurate vehicle classification but also provides supplementary energy recovery, pointing toward the development of energy-positive charging stations in the future. These findings imply that future charging networks can benefit from combining intelligent algorithms with physical energy-harvesting systems to achieve both cost-effectiveness and sustainability. Moreover, the system's user-centric interface, offering live cost and slot availability, is directly applicable to real-world deployment, ensuring scalability for urban environments. Overall, our study demonstrates that the proposed framework not only addresses immediate operational issues but also provides a foundation for next-generation charging systems capable of supporting the rapid growth of electric mobility.

Table 3. Summary of key findings from the proposed smart EV charging system

Parameter	Conventional charging system	Proposed system (ML+pressure pads)	Improvement/observation
Average slot utilization (%)	68	89	Better optimization through ML-based allocation
Average waiting time (minutes)	32	14	~56% reduction due to adaptive scheduling
Forecasting accuracy (demand prediction, %)	74	92	LSTM significantly improves prediction accuracy
energy recovery (from pressure pads, kWh/day)	–	21	Additional sustainable energy contribution
Average SoC at exit (%)	74	84	Higher and more consistent charging outcomes
User satisfaction (survey-based, %)	70	88	Enhanced by smart display and real-time slot guidance
Operational cost (per session, INR)	112	93	Cost reduction through demand-aware scheduling

The revised results and discussion section has been organized to clearly connect the study's findings with its objectives and the broader research context. It begins with an overview of the main outcomes, including improvements in slot utilization, reductions in waiting times, enhanced forecasting accuracy, and supplementary energy recovery, to provide readers with a concise snapshot of the system's performance. The discussion then examines tariff forecasting and demand prediction, showing how the LSTM model achieves higher accuracy compared with existing approaches and emphasizing its implications for cost reduction and demand-aware scheduling. Following this, the efficiency of slot allocation is presented, supported by summary tables, and interpreted in terms of how ML–based allocation improves infrastructure utilization and user experience compared to conventional systems. Battery SoC behavior and user charging preferences are also analyzed, highlighting typical charging patterns across different vehicle types and discussing how these patterns can inform the design of future charging networks. Another key focus is the contribution of energy recovery through pressure pads, where the harvested energy is quantified and compared with related energy-harvesting studies, demonstrating its potential for more sustainable, energy-positive charging stations. To situate the findings within the scientific community, the section includes a direct comparison with prior studies, emphasizing how the integration of sensing technology and ML extends beyond earlier work on scheduling or energy harvesting in isolation. Finally, the discussion addresses practical implications, such as applications in smart grids and urban mobility systems, while also acknowledging limitations including scalability, sensor calibration challenges, and reliance on historical data. The section concludes by suggesting future research directions, including integrating renewable energy sources, applying reinforcement learning for adaptive scheduling, and testing the system in larger-scale pilot deployments.

4. CONCLUSION

This study has demonstrated that combining ML with pressure pad technology offers a powerful solution to some of the most pressing challenges in EV charging infrastructure. By integrating random forest, K-means clustering, and LSTM forecasting with real-time sensing and energy harvesting, the proposed system not only improves slot allocation efficiency and reduces waiting times but also contributes to sustainability through supplementary energy recovery. These findings carry important implications for the EV research community, as they highlight the value of merging intelligent data-driven algorithms with physical sensing technologies to build more adaptive, user-centric, and energy-positive charging networks. Beyond proving feasibility, our work suggests several practical applications: urban charging stations can adopt pressure pad–based detection for accurate demand estimation; utilities can use demand-aware ML models to reduce peak grid stress; and operators can deploy smart display interfaces to improve user transparency and trust. At the same time, this research opens opportunities for further investigation. Future work may focus on scaling the system to larger networks, integrating additional renewable sources, enhancing sensor calibration to reduce variability, and applying reinforcement learning for even more adaptive scheduling under uncertain conditions. Ultimately, our findings show that intelligent, sustainable charging stations are not only technically achievable but also essential for supporting the rapid transition toward widespread EV adoption, offering benefits to users, operators, and the broader power grid.

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AUTHOR CONTRIBUTIONS STATEMENT

This journal uses the Contributor Roles Taxonomy (CRediT) to recognize individual author contributions, reduce authorship disputes, and facilitate collaboration.

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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

The data that support the findings of this study were collected from reputable online repositories, peer-reviewed articles, and expert academic discussions. The data sets are available from the authors, Tadi Kumara Swamy, G. Swapna upon reasonable request.

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