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A Survey on Real-Time EV Charging Station Management System

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***Abstract*—The escalating adoption of Electric Vehicles (EVs) has brought the limitations of current Charging Station Management Systems (CSMS) into sharp focus. Existing infrastructure, which typically provides drivers with only a basic binary status such as "Available" or "In Use," is insufficient for the dynamic and time-sensitive demands of a high-density EV ecosystem. This lack of granular, real-time insight forces drivers to waste valuable time and energy navigating to congested stations, intensifying range anxiety and reducing confidence in electric mobility. Moreover, such passive systems lead to inefficient utilization, creating persistent congestion at certain stations while others remain underused. To address these shortcomings, we propose the Smart Real-Time EV Charging Station Management System, an advanced AI-powered framework designed to transform the charging experience. The system integrates multiple dynamic data streams, including live station status, real-time traffic information, and vehicle-specific parameters such as battery State-of-Charge (SoC) and current location. Using sophisticated Machine Learning (ML) models, it moves beyond binary indicators to generate predictive availability forecasts, estimating precisely when a charging point will become free. A multi-factor optimization algorithm then combines predicted waiting time (T_{Wait}), real-time travel duration (T_{Travel}), and driver charging needs to provide the most time-efficient station recommendation. By balancing individual user requirements with overall network load, the system enhances convenience, reduces congestion, and increases charging infrastructure efficiency.**

I. INTRODUCTION

The global shift toward electric mobility has intensified the need for efficient and intelligent Electric Vehicle (EV) Charging Station Management Systems (CSMS). Existing solutions in both academia and industry expose critical shortcomings in addressing real-time availability, driver convenience, and network optimization. Most current systems fall under two main categories: Grid-Centric Management Systems and Basic Information or Reservation Platforms, both of which fail to meet the practical and dynamic needs of an expanding EV ecosystem.

Grid-centric systems, while vital for maintaining energy balance through Vehicle-to-Grid (V2G) operations and demand response mechanisms, primarily focus on optimizing load distribution from the perspective of utility providers. As a result, these systems often overlook essential user-centric factors, leading to rigid scheduling, unpredictable waiting times, and limited visibility into charging patterns. This creates significant inconvenience for EV drivers, heightens range anxiety, and undermines the reliability of public charging infrastructure. On the other hand, basic information platforms only provide static or binary charging statuses, such as "Available" or "In Use." Even advanced reservation-based systems lack predictive intelligence and fail to incorporate dynamic real-world variables like fluctuating traffic conditions, historical station congestion, user charging behavior, or vehicle-specific metrics such as State of Charge (SoC), battery temperature, or energy consumption trends.

To overcome these limitations, the proposed Smart Real-Time EV Charging Station Management System integrates Artificial Intelligence (AI) and Machine Learning (ML) to deliver predictive availability, accurate wait-time estimation, and personalized recommendations. By combining real-time station data, live traffic APIs, and vehicle telematics, the system provides a proactive user experience tailored to individual needs. Unlike traditional systems, this approach enables intelligent forecasting, optimized routing, and balanced charging station utilization. This report details the motivation, design methodology, and operational framework of the proposed system, highlighting its potential to significantly enhance user satisfaction, improve infrastructure efficiency, and accelerate large-scale EV adoption through a more reliable and data-driven charging ecosystem.

II. Literature Review

Existing research shows a clear shift from static models to intelligent, data-driven approaches that use AI and ML for predicting availability, optimizing routing, and forecasting demand in EV charging networks.

[1] A. Kumari (2024): This study developed a predictive machine learning model to forecast both availability and expected wait times at EV charging stations. The model integrates features such as station location, charger type, historical usage, traffic data, and environmental factors. Random Forest, Linear Regression, and Long Short-Term Memory (LSTM) models were compared, achieving 87.4% accuracy and a 7.8-minute average error. The work demonstrated that multi-source data fusion can improve user experience and optimize charging infrastructure in urban environments.

[2] F. Soldan et al. (2021): This paper presented a big data streaming architecture for short-term availability prediction. Using logistic regression models updated continuously with real-time streaming data, the system adapts to changing patterns such as traffic fluctuations and local events. It outperformed static historical approaches, highlighting the value of adaptive learning for congestion mitigation.

[3] R. Luo et al. (2022): The authors proposed a deep graph neural network—AST-GIN (Attribute-Augmented Spatial-Temporal Graph Informer Network)—that integrates spatial and temporal features across stations. Combining GCNs with Informer attention, the model leverages weather, POIs, and temporal patterns, outperforming LSTM and GRU baselines. The study showed the scalability of graph-based spatiotemporal prediction.

[4] M. Manai et al. (2024): This work merged availability prediction with recommendation algorithms to provide personalized charging suggestions. An ANN-based prediction model and a ranking engine evaluated distance, predicted free time, and congestion levels. Using real-world API datasets, the system improved F1-score by 9%, establishing a foundation for user-centric charging recommendations.

[5] A. Sreekumar and R. Lekshmi (2024): The authors focused on short-term demand forecasting using Random Forest, XGBoost, and CatBoost models on Indian charging station data. CatBoost achieved the best performance with RMSE = 0.10, emphasizing its robustness for mixed data types. The study highlighted the importance of accurate demand forecasting for grid stability and dynamic station allocation.

[6] A. Hussain et al. (2025): This paper introduced a hybrid Transformer-LSTM model for medium- and long-term charging demand forecasting. Trained on the ACN dataset (Caltech and JPL), the model captured both short-term variations and long-term seasonal trends. It reduced MAE by 17% and MSE by 20% compared to standard LSTM models, contributing to predictive scheduling and sustainable energy management.

[7] S. Schoenberg and F. Dressler (2021): This study addressed waiting-time reduction through adaptive route planning. The authors proposed a Central Charging Station Database (CSDB) enabling vehicles to coordinate charging stops and predict congestion. The adaptive routing algorithm considers distance, charging duration, and waiting time, achieving up to 97% reduction in average waiting times in simulations.

[8] R. Gopalakrishnan et al. (2016): A foundational study combining multi-view learning with optimization theory to improve charging station placement and demand estimation. Using Canonical Correlation Analysis (CCA), the authors integrated traffic density, POIs, and historical usage patterns. Their mixed-packing-and-covering optimization achieved 10–20% improvement in demand satisfaction compared to heuristic baselines.

[9] J. Hecht et al. (2021): This paper explored ensemble ML models such as Gradient Boosting and Random Forests for predicting station occupancy. Incorporating temporal and spatial variables, the system achieved 94.8% accuracy on real-world datasets. The study served as one of the early demonstrations of supervised learning for operational forecasting in EV charging networks.

[10] P. D. Sawant (2025): This paper analyzed Agentic AI systems designed for autonomous real-time decision-making using continuous feedback and self-optimizing mechanisms. The study showed that agentic models outperform traditional AI in dynamic conditions by adapting instantly to changing inputs. Its relevance to EV charging networks is significant, as agentic AI can autonomously manage load distribution, update availability predictions, and optimize user recommendations without manual intervention.

III. Summary Table

Ref.	Authors	Focus Area	Key Technique / Model	Outcome	Relevance to Smart EV System
1	A. Kumari (2024)	Availability & wait-time prediction	Random Forest, Linear Regression, LSTM	87.4% accuracy, avg. 7.8 min wait-time error	Core ML layer for predictive charging-slot availability
2	F. Soldan et al. (2021)	Real-time occupancy forecasting	Streaming Logistic Regression	Improved short-term occupancy forecast via live data adaptation	Enables real-time station status updating
3	R. Luo et al. (2022)	Spatio-temporal availability prediction	AST-GIN (Graph + Informer Network)	+10% forecasting gain vs LSTM/GRU, scalable to city-wide grids	Supports multi-station prediction & temporal mapping
4	M. Manai et al. (2024)	Personalized station recommendation	ANN + Real-time Recommender System	9% higher F1-score over baselines; dynamic route suggestions	Provides driver-centric recommendations
5	A. Sreekumar & R. Lekshmi (2024)	Demand prediction & load balancing	XGBoost, CatBoost Regression	RMSE = 0.10, improved short-term load estimation	Assists grid optimization & congestion control
6	A. Hussain et al. (2025)	Medium/long-term demand forecasting	Hybrid Transformer-LSTM	MAE ↓17%, MSE ↓20% vs LSTM alone	Enables long-term scheduling & capacity planning
7	S. Schoenberg & F. Dressler (2021)	Route optimization & waiting-time reduction	Adaptive Routing Algorithm + CSDB	Up to 97% reduction in average waiting times	Integrates routing & station-load balancing
8	R. Gopalakrishnan et al. (2016)	Station placement & demand optimization	Multi-View Learning + CCA + Mixed Packing/Covering Optimization	10–20% better demand coverage vs heuristics	Optimizes charging network layout and equity
9	J. Hecht et al. (2021)	ML-based occupancy classification	Gradient Boosting, Random Forest	94.8% prediction accuracy on real-world data	Baseline for AI-driven availability forecasting
10	P. D. Sawant (2025)	Agentic AI for autonomous optimization	Autonomous decision-making, self-optimizing agents	Improved real-time resource allocation and dynamic adaptation	Enables autonomous load balancing and adaptive EV station management

IV. Future Work

While significant progress has been made in predictive modeling, optimization, and real-time management of EV charging infrastructure, several research challenges remain open for exploration.

1) **Integration of Multi-Modal Data:** Future work should incorporate heterogeneous real-time data sources such as driver profiles, vehicle battery health, charging behavior, and renewable energy input. This integration would improve prediction precision and adaptive scheduling.
2) **Edge and Federated Learning:** Deploying edge AI at charging stations can reduce latency and dependency on centralized servers. Federated learning models can preserve user privacy while enabling distributed training across multiple charging networks.
3) **Dynamic Pricing and Demand Response:** Integrating predictive availability models with economic incentive systems could enable adaptive pricing mechanisms that encourage users to charge at underutilized stations, balancing network load efficiently.
4) **Reinforcement Learning for Global Optimization:** Future systems could apply multi-agent reinforcement learning (MARL) to coordinate multiple EVs and stations, dynamically optimizing routing, scheduling, and energy allocation across an entire network.
5) **Integration with Smart Grids and Renewable Energy:** The next generation of EV management systems should include bi-directional Vehicle-to-Grid (V2G) features to stabilize power flow and store renewable energy. Predictive charging aligned with grid demand forecasts could enhance sustainability.
6) **User Experience and Personalization:** Future research should address user-centric personalization—such as predicting driver preferences, range anxiety thresholds, and integrating AI-driven recommendation engines into mobile applications.
7) **Scalability and Real-World Testing:** To transition from simulation to deployment, future work must emphasize real-world testing across cities and varied geographic contexts. Pilot programs integrating prediction, routing, and pricing modules will validate scalability and robustness.
8) **Cybersecurity and Data Privacy:** As data-driven EV systems expand, maintaining security and protecting sensitive user and vehicle data will be vital. Blockchain and cryptographic protocols could support secure, transparent, and tamper-proof data transactions between stations and vehicles.

References

[1] A. Kumari, "Machine Learning-based Prediction Model for EV Charging Station Availability and Waiting Time," IEEE ITS, 2024.

[2] F. Soldan et al., "Real-time Big-data Streaming Architecture for EV Station Occupancy," SETA, 2021.

[3] R. Luo et al., "AST-GIN for Charging Station Forecasting," ACM SIGKDD, 2022.

[4] M. Manai et al., "ANN-based Personalized EV Charging Recommendation," JCP, 2024.

[5] A. Sreekumar & R. Lekshmi, "Short-term Demand Forecasting for EV Networks," Energy Reports, 2024.

[6] A. Hussain et al., "Hybrid Transformer-LSTM for EV Demand," Applied Energy, 2025.

[7] S. Schoenberg & F. Dressler, "Adaptive Route Planning for EV Charging," IEEE TVT, 2021.

[8] R. Gopalakrishnan et al., "EV Station Placement Optimization," TRC, 2016.

[9] J. Hecht et al., "Ensemble-learning for Occupancy Classification," Energy and AI, 2021.

[10] P. D. Sawant, "Agentic AI: A Quantitative Analysis of Performance and Applications," Journal of Applied Artificial Intelligence (JAAI), vol. 3, no. 2, pp. 41–52, 2025.