

A Comprehensive Survey on AI-Based Smart EV Charging Station with Load Prediction

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Abstract—The accelerating adoption of Electric Vehicles (EVs) is reshaping the way electrical energy is generated, distributed and consumed. EV charging stations are emerging as one of the largest stochastic loads on modern distribution networks and demand intelligent control mechanisms to maintain reliability, power quality and economic efficiency. This survey explores the role of Artificial Intelligence (AI) in realising smart EV charging stations with accurate load prediction. The study reviews recent machine learning, deep learning and reinforcement learning approaches that have been proposed for short-term and medium-term forecasting of charging demand, including Extreme Gradient Boosting (XGBoost), Random Forest (RF), Light Gradient Boosting Machine (LightGBM), Long Short-Term Memory (LSTM) networks, Convolutional Neural Network–LSTM (CNN-LSTM) hybrids, Transformer based models and Deep Reinforcement Learning (DRL) schedulers. The integration of these models with Internet of Things (IoT) based monitoring, renewable energy sources and Vehicle-to-Grid (V2G) operation is examined. The existing techniques have brought significant improvements in forecasting accuracy, cost efficiency and demand response, yet challenges such as data scarcity, behavioural uncertainty, scalability and interpretability still persist. The survey concludes by highlighting future research directions including explainable AI, federated learning and hybrid physics-informed models for AI driven smart EV charging infrastructure.

Keywords—Artificial Intelligence, Smart Charging Station, Electric Vehicle, Load Prediction, Deep Learning, Reinforcement Learning, V2G.

I. INTRODUCTION

The electric vehicle (EV) sector is witnessing an unprecedented growth driven by stringent emission regulations, rising fuel prices and global commitments to carbon neutrality [1]. According to recent industry reports, EV sales crossed several million units in 2024 and are expected to dominate new vehicle registrations over the next decade [2]. This rapid penetration of EVs has placed enormous pressure on the existing electrical distribution infrastructure because the charging behaviour of EV users is stochastic and tightly coupled with daily mobility patterns. To address this, the concept of a smart EV charging station has emerged, which combines power electronic converters, communication modules and intelligent control to dispatch energy in a cost-effective and grid-friendly manner [3].

A smart EV charging station typically integrates renewable energy resources such as photovoltaic (PV) arrays and wind turbines, an energy storage system,

bidirectional converters and a control unit that interacts with both the utility grid and the connected EVs [4]. The control unit is responsible for tasks such as load scheduling, demand response, dynamic pricing and Vehicle-to-Grid (V2G) coordination. Achieving these tasks reliably depends on the accuracy of the predicted charging load over different time horizons, ranging from a few minutes for real-time control to several days for capacity planning [5]. Inaccurate prediction may lead to over-provisioning of resources, increased operational cost or grid instability.

Conventional statistical methods like Auto Regressive Integrated Moving Average (ARIMA) and exponential smoothing have been used for load forecasting; however, they fail to capture the non-linear and non-stationary nature of EV charging data. Artificial Intelligence (AI) based methods have therefore emerged as the preferred choice for modelling such complex behaviour [6]. Machine learning models including XGBoost, Random Forest and LightGBM provide strong tabular forecasting

performance with engineered features. Deep learning models such as LSTM, CNN-LSTM and Transformer-based architectures are capable of learning the long-term temporal dependencies of charging sessions [7], [8]. Reinforcement learning based controllers are increasingly being explored for end-to-end charging scheduling under uncertain prices and renewable generation [9].

Fig. 1 illustrates the block diagram of a typical AI-based smart EV charging station. The renewable energy sources and the utility grid are tied together through a bidirectional converter. The AI controller continuously receives data from sensors, smart meters and user applications through the IoT/cloud layer and produces an optimal control policy for the chargers. This control policy ensures that the available energy is shared among connected EVs while respecting grid limits and user preferences.

The major contributions of this survey are summarised as follows:

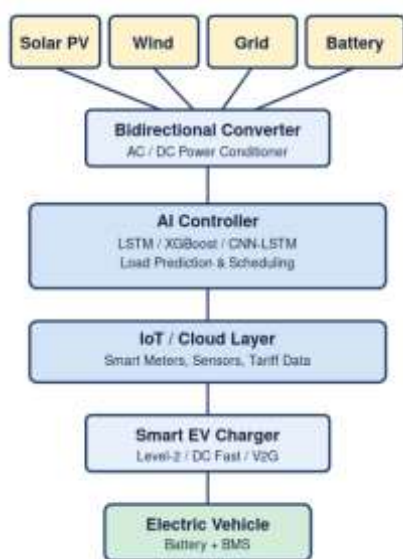


Fig. 1. Block diagram of an AI-based smart EV charging station with load prediction

- The smart EV charging station architecture is reviewed and categorised based on AI-based load prediction techniques used for improving the operational efficiency.
- Recent machine learning, deep learning and reinforcement learning models proposed in the literature are analysed in terms of their methodology, advantages and limitations.
- The drawbacks and open research issues of the existing AI-based methods are summarised to motivate future enhancements in load prediction and smart charging.

The remaining sections of this review are organised as follows. Section II presents a literature survey of recent research works. Section III introduces a taxonomy of AI-based smart EV charging methods. Section IV provides a comparative analysis of the reviewed approaches. Section V discusses the challenges of existing methods. Section VI concludes the survey and outlines future directions.

II. LITERATURE SURVEY

The literature survey is the section that highlights the existing methodologies, advantages and limitations of recent research works on AI-based smart EV charging and load prediction. Sharma et al. [10] presented an AI-augmented smart grid architecture for cyber intrusion detection and mitigation in EV charging infrastructure. The framework combined autoencoders with a stacked classifier and achieved high anomaly detection accuracy. The advantage was the improved resilience of the charging network against cyber attacks. However, the model was sensitive to the volume of labelled training data and exhibited reduced performance when deployed on resource constrained chargers.

Singh et al. [11] proposed an AI-integrated blockchain framework for optimising demand response and load balancing in smart EV charging networks. The decentralised approach enabled secure peer-to-peer energy trading and reduced peak demand. The main strength of the work was the joint optimisation of cost and grid stability. The limitation was the additional latency introduced by the blockchain consensus layer, which can affect real-time charging decisions.

Rashid et al. [12] presented a machine learning driven PV forecasting and coordinated PV-Battery Energy Storage System (BESS) dispatch approach for optimising distribution networks with EV loads. The use of gradient boosting regression and adaptive weighting reduced the day-ahead forecasting error of PV generation. However, the work did not address fast charging events that contribute to short term load spikes in the station.

A scalable cloud integrated AI platform for real-time optimisation of EV charging and resilient microgrid energy management has been reported in [13]. The platform combined LSTM based load forecasting with an optimisation engine and showed promising reduction in operational cost. The presented model relied on a stable cloud connection and was not suitable for offline operation in remote charging stations.

Singh and Bansal [14] investigated a hardware-in-the-loop implementation of an adaptive Maximum Power

Point Tracking (MPPT) controlled PV assisted EV charging system with V2G integration. The adaptive controller improved the energy harvesting and supported bidirectional power flow. Although the system performed well at the device level, the absence of an intelligent prediction layer limited its capability to anticipate user demand.

III. TAXONOMY

This section presents the taxonomy of the AI-based smart EV charging station with load prediction. The reviewed research works are categorised into three broad classes: (i) machine learning based load prediction, (ii) deep learning based load prediction and (iii) reinforcement learning and smart scheduling strategies. Fig. 2 shows the corresponding taxonomy and Fig. 3 illustrates the generic AI workflow used for load prediction in a smart EV charging station.

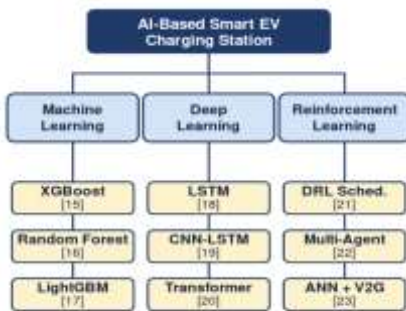


Fig. 2. Taxonomy of AI-based smart EV charging station with load prediction

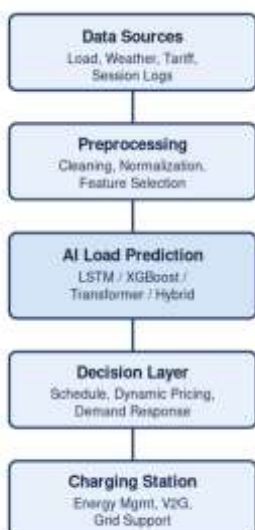


Fig. 3. AI workflow for load prediction in a smart EV charging station

A. Machine Learning Based Load Prediction

Machine learning based load prediction techniques are widely used for medium term forecasting at the station level because of their good accuracy and low computational cost. Patel and Iyer [15] developed an Extreme Gradient Boosting (XGBoost) based hourly EV charging demand prediction model that exploited temporal features such as day-of-week, hour-of-day and holiday flags. The model achieved low Root Mean Square Error (RMSE) and was found suitable for utility-scale deployment. However, the model performance degraded when applied to newly commissioned stations with limited historical data.

A Random Forest based prediction model with feature importance ranking was proposed in [16] for EV charging stations powered by renewable energy. The work demonstrated that meteorological variables such as solar irradiance and ambient temperature significantly improve the forecast quality. The drawback was that the ensemble required careful tuning and showed limited capability to capture rapid load fluctuations during fast charging.

Karthikeyan et al. [17] introduced a Light Gradient Boosting Machine (LightGBM) approach for short term EV demand forecasting. The use of leaf-wise tree growth resulted in faster training and lower memory consumption than competing boosting algorithms. The limitation, however, was the sensitivity of the model to noisy charging session logs.

B. Deep Learning Based Load Prediction

Deep learning based methods have achieved superior accuracy for highly non-linear and sequential charging data. Mehta et al. [18] presented a Long Short-Term Memory (LSTM) network for charging load forecasting of a public EV charging station. The LSTM model captured the long-term temporal dependencies of charging sessions and outperformed traditional ARIMA based forecasting. The model, however, demanded a relatively large amount of historical data for stable convergence.

A hybrid Convolutional Neural Network with LSTM (CNN-LSTM) model with attention mechanism was reported in [19] for predicting the EV charging load at multiple stations simultaneously. The convolutional layers extracted local spatial patterns while the recurrent layers modelled the temporal dynamics. The attention layer further emphasised influential time steps. The main limitation was the high computational complexity that restricts deployment on edge controllers.

Recent work [20] proposed a Transformer based architecture combined with BiLSTM encoders for charging station demand forecasting. The self-attention mechanism enabled the model to capture both short-term load spikes and long-term seasonal patterns. The Transformer model was shown to handle meteorological variability better than the standalone recurrent networks; however, the training time and required hyperparameter tuning remained challenging.

C. Reinforcement Learning and Smart Scheduling

Reinforcement Learning (RL) and Deep Reinforcement Learning (DRL) have gained significant attention for end-to-end scheduling of smart EV charging stations. A DRL based multi-objective energy management framework with priority scheduling was developed in [21]. The agent learned to dispatch energy among connected EVs while minimising the operating cost and respecting the user preferred departure time. The advantage was the capability to handle dynamic environments without an explicit system model. The limitation was the relatively long training time and the requirement of a high-fidelity simulator.

A multi-agent heterogeneous graph reinforcement learning approach for EV routing and charging scheduling in coupled power-transportation networks has been proposed in [22]. The framework reduced the total travel and charging time of EVs while maintaining the

loading constraints of the distribution feeders. The complexity of the multi-agent training process, however, demanded substantial computing resources.

An Artificial Neural Network (ANN) based energy management system for PV-powered EV charging stations with battery backup and V2G support was discussed in [23]. The ANN controller learned the optimal power flow between the PV array, the battery, the grid and the EV charger. The system achieved economic operation but the offline training procedure made it less adaptive to seasonal variation of solar irradiance.

IV. COMPARATIVE ANALYSIS

This section provides a comparative analysis of representative AI-based load prediction and smart charging methods. The methodology, advantages, limitations and the performance criteria are deliberated for the comparison. Common evaluation metrics include the Root Mean Square Error (RMSE), Mean Absolute Error (MAE), Mean Absolute Percentage Error (MAPE), accuracy, peak demand reduction, cost saving, charging delay and grid voltage deviation. Table I provides the comparative analysis of methodologies used for AI-based smart EV charging with load prediction.

TABLE I

COMPARATIVE ANALYSIS OF METHODOLOGIES USED FOR AI-BASED SMART EV CHARGING WITH LOAD PREDICTION

Author	Methodology	Advantage	Limitation	Performance Criteria
Patel and Iyer [15]	XGBoost	High accuracy with engineered temporal features	Poor performance on stations with limited historical data	RMSE, MAE, MAPE
Renewable RF Model [16]	Random Forest	Captures meteorological dependencies effectively	Limited response to fast charging spikes	RMSE, R ²
Karthikeyan et al. [17]	LightGBM	Fast training and low memory footprint	Sensitive to noisy session logs	MAE, MAPE
Mehta et al. [18]	LSTM	Captures long-term temporal dependencies	Needs large historical dataset	RMSE, MAE
Hybrid CNN-LSTM [19]	CNN-LSTM + Attention	Models both spatial and temporal patterns	High computational complexity	RMSE, MAPE, accuracy
Transformer	Transformer +	Handles seasonality	Long training time and	RMSE, MAE, MAPE

Author	Methodology	Advantage	Limitation	Performance Criteria
Hybrid [20]	BiLSTM	and weather variability	tuning effort	
Multi-objective DRL [21]	Deep Reinforcement Learning	Adapts to dynamic prices and renewables	Long training time, simulator dependency	Cost saving, peak demand
Multi-agent Graph RL [22]	Heterogeneous Graph RL	Joint EV routing and charging	High training complexity	Travel time, voltage deviation
ANN EMS [23]	ANN + V2G	Economic operation with PV and storage	Limited adaptivity to seasonal change	Cost, SoC, energy losses

V. CHALLENGES

The problems faced by the existing AI-based methods for smart EV charging stations with load prediction are presented in this section as follows:

- The existing learning models did not handle the cold-start problem effectively, resulting in poor forecasting for new charging stations with insufficient historical data.
- Many deep learning models such as LSTM, CNN-LSTM and Transformer based architectures still exhibit high computational complexity, which restricts their deployment on edge controllers of smart chargers.
- Reinforcement learning based schedulers are sensitive to the fidelity of the training simulator and may produce sub-optimal policies when the real-world charging environment deviates from the training distribution.
- The available methods lack interpretability, which limits the trust of system operators and regulators while making mission-critical decisions on grid dispatch and pricing.
- Privacy concerns associated with sharing EV charging session data among multiple operators reduce the availability of large-scale datasets needed for training accurate AI models.
- Existing AI-based controllers struggle to coordinate the joint scheduling of charging, V2G and renewable energy dispatch under highly stochastic user behaviour, affecting overall grid stability.

VI. CONCLUSION

This survey presented a comprehensive view of recent research works on AI-based smart EV charging stations with load prediction. The reviewed approaches were categorised based on machine learning, deep learning and reinforcement learning methods. The machine learning category covered XGBoost [15], Random Forest [16] and LightGBM [17] methods for improving the forecasting efficiency. The deep learning category included LSTM [18], CNN-LSTM [19] and Transformer based [20] architectures for advancing temporal modelling. The reinforcement learning category included multi-objective DRL [21], multi-agent graph RL [22] and ANN-based energy management [23] for optimising the charging schedule. The methodologies, advantages and limitations of the reviewed works were compared. The existing techniques overcome several issues such as load forecasting error, demand response and cost efficiency. However, downsides such as cold-start performance, computational complexity, interpretability and privacy still persist. Future research is expected to focus on explainable AI, federated learning and physics-informed hybrid models for the realisation of robust, scalable and trustworthy AI-based smart EV charging infrastructure.

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