



A Survey on Machine Learning–Driven Classification for Optimized EV Battery Charging

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ABSTRACT:

Efficient and battery-friendly electric vehicle (EV) charging is essential for maximizing battery life, reducing energy costs, and maintaining grid stability. This paper introduces a machine learning driven framework for optimized EV battery charging, focused on predicting ideal charging durations using supervised classification techniques. Key input features such as initial state of charge (SoC), ambient temperature, charging power level, and historical usage data are extracted and preprocessed from a real-world EV dataset. Multiple classifiers k-Nearest Neighbors (KNN), Random Forest (RF), and Support Vector Machine (SVM) are trained to categorize charging sessions into discrete time classes that support battery health goals. Stratified cross-validation is used to assess model performance based on accuracy, F1-score, and recall. The top-performing model is integrated into a smart scheduler that dynamically recommends personalized charging durations, balancing user convenience with battery longevity. This adaptive approach promotes intelligent home and public charging infrastructure. Future work aims to include real-time grid data and extend the system to support multi-objective scheduling under dynamic electricity tariffs.

Keywords: Electric Vehicle Charging Machine Learning Classification, Battery Health Optimization, Charging Duration Prediction, Adaptive Charging Scheduler

1. INTRODUCTION:

Rapid growth of electric vehicles (EVs) has marked a significant shift in the transportation sector toward sustainable and environmentally friendly alternatives to conventional fossil-fuel-powered vehicles. As the adoption of EVs accelerates globally, efficient management of battery charging processes becomes crucial to enhance battery lifespan, reduce charging time, and optimize energy consumption. Battery charging optimization not only affects the performance and durability of EV batteries but also plays a vital role in the overall energy management system, contributing to grid stability and user convenience. Machine learning (ML), a subset of artificial intelligence, has emerged as a powerful tool for addressing complex problems in various domains by enabling systems to learn from data and make intelligent decisions. In the context of EV battery charging, ML-driven classification techniques offer promising capabilities to predict optimal charging parameters, classify charging states, and adaptively control the charging process based on real-time conditions and historical data. This approach helps in mitigating issues such as overcharging, thermal runaway, and inefficient energy usage. Machine learning (ML) offers transformative potential in this domain by enabling predictive and adaptive control of EV charging. Through classification techniques, ML models can identify battery states, forecast optimal charging parameters, and adjust charging protocols in real time based on historical data and environmental inputs. This helps prevent issues like overcharging and thermal stress while improving energy efficiency. As ML continues to evolve, its integration into EV charging systems will be key to building resilient, intelligent energy ecosystems that support both consumer needs and broader sustainability goals.

2. LITERATURE SURVEY

[1] Soumya Sathyan et al. (2025) designed a hybrid multi-criteria decision-making and multi-objective framework for optimal sizing of PV-powered EV charging stations. The system used MOPSO and hybrid MCDM to balance economic, environmental, and social aspects. The research gap identified is that most existing studies ignored social and environmental factors and lacked an integrated optimization framework. [2] Nada El-Ayi et al. (2023) developed a hybrid 1D-CNN + LSTM model for estimating the State of Charge (SoC) and State of Health (SoH) of EV batteries. The study achieved higher accuracy from real-world data. The limitation is that SoC and SoH are mostly predicted separately, and temporal-spatial dependencies remain underutilized. [3] Sarthak Agrawal et al. (2023) analysed lithium-ion battery aging under dynamic driving conditions using machine learning. The model predicted capacity degradation effectively. The gap identified is that most previous studies used static lab data and lacked focus on dynamic real-world conditions. [4] Andrea Trivella et al. (2022) proposed a numerical simulation model representing the collective behaviour of EV users at charging points to improve grid load and energy dispatch. The research gap is that aggregation of EV population behaviour is underexplored, and mixed EV characteristics are rarely modelled. [5] S. Chakraborty et al. (2023) introduced a federated and ensemble learning framework for accurate and secure estimation of EV battery State of Health (SoH). The advantage is privacy preservation and distributed learning. The limitation is that few studies combine federated and

ensemble methods for real-time SoH estimation. [6] Prerna Jain and Sanjeev Kumar (2023) proposed a neural network-based model to predict the Remaining Useful Life (RUL) and capacity fade of lithium-ion batteries. The strength is simultaneous RUL and capacity prediction, while the limitation is the lack of generalization across different datasets. [7] Silvana Matrone et al. (2023) developed a K-Nearest Neighbours (KNN) classification model to predict EV charging session duration for optimized battery performance. The system achieved high accuracy using limited input data. The gap found is that most models use regression instead of classification and lack deploy ability on individual stations. [8] Adnan Kavak and Savaş Berk Başlamışlı (2022) applied machine learning models such as Random Forest and Gradient Boosting to predict energy consumption for electric city buses. The study improved energy efficiency but noted that most models lacked route-specific adaptability under varying traffic conditions. [9] Kamlesh Kumar and Kritika Singh (2023) optimized EV charging schedules using machine learning, considering driver satisfaction factors like cost and waiting time. The advantage is inclusion of user parameters, while the gap is that previous models ignored real-time adaptability and user preferences. [10] S. K. Kollimalla et al. (2023) proposed a rule-based dynamic scheduling model for grid-integrated EVs to balance power supply and demand. The work improved grid coordination, but the limitation is poor adaptability to sudden load variations. [11] Atta Ul Mustafa et al. (2023) developed a machine learning-based SoC estimation model for light EVs using active power data. The advantage is accurate prediction with minimal sensors. The limitation is that most SoC models are complex and unsuitable for real-time use. [12] Lu Yu et al. (2023) applied an Extreme Learning Machine (ELM) algorithm for SoC prediction of electric loader batteries. The system achieved faster computation and improved accuracy. The gap is that SoC prediction for heavy-duty EVs like loaders is underexplored. [13] Xinxin Pan et al. (2023) proposed an improved Transformer model for predicting the Remaining Useful Life (RUL) of Li-ion batteries. The model captured long-term temporal patterns effectively. The limitation is that long-term RUL prediction remains challenging due to data sparsity. [14] V. Vaidehi et al. (2023) developed a hybrid SoC estimation model combining Coulomb counting and machine learning for real-time applications. The system minimized cumulative error but noted that hybrid approaches are still rarely adopted for adaptive charging scenarios.

3. METHODOLOGY:

The proposed system for Machine Learning–Driven Classification for Optimized EV Battery Charging is designed to develop an intelligent, data-driven framework that predicts optimal charging durations, improves battery health, and enhances energy efficiency. The methodology is divided into three main stages: Input, Processing, and Output, ensuring systematic data handling, learning, and real-time decision-making.

This modular design enables scalability, flexibility, and adaptability for both individual and large-scale charging systems. The methodology framework integrates multiple algorithms—classification, feature engineering, and optimization—to achieve accurate, balanced, and practical EV charging recommendations.

Input Stage

The **input stage** involves collecting comprehensive real-time data from electric vehicles and their charging environments. The system utilizes multiple data sources such as:

- **Battery Management System (BMS) logs:** capturing parameters like State of Charge (SoC), voltage, current, and temperature.
- **Charger telemetry:** including charger type, power rating, and charging profile.
- **Vehicle telematics:** providing contextual information such as speed, ambient temperature, and driving patterns.
- **Session metadata:** including start and end time, target SoC, and user preferences.
- **External data:** such as weather and grid load, for adaptive decision-making.

This data forms the foundation for the classification and optimization process.

Processing Stage

The **processing stage** is the core of the system, where data is cleaned, labeled, modeled, and optimized. It includes several key operations:

1. Data Preprocessing

All raw data is standardized into uniform formats and units. The following preprocessing steps are performed:

- Removal of missing, duplicate, and noisy records.
- Time synchronization of data from multiple sources.
- Noise filtering and smoothing using statistical methods.
- Feature extraction such as charges rates, temperature rise, and energy delivered.
- Encoding of categorical attributes (e.g., vehicle model, charger type). This ensures data consistency and readiness for model training.

2. Sampling and Data Splitting

The dataset is divided into three subsets—Training (70%), Validation (15%), and Testing (15%).

Temporal splitting ensures that earlier sessions are used for training and the latest for testing, preventing data leakage.

Group-wise splitting based on vehicle IDs maintains independence between sessions, and stratified sampling ensures balanced class representation.

3. Labelling

Charging sessions are labelled into meaningful classes to enable supervised learning:

- **Charging Type:** Fast, Balanced, or Trickle Charging.
- **Battery Risk Levels:** Safe, Overheat Risk, or Degradation Risk.

Labels are assigned using domain-specific rules (for example, temperature $> 55^{\circ}\text{C}$ $\rightarrow$ Overheat) and verified by expert annotation. An active learning approach is used to refine ambiguous cases efficiently.

4. Model Development

The proposed system employs several machine learning algorithms to classify charging sessions and predict optimal parameters:

K-NearestNeighbours

A baseline algorithm that groups charging sessions with similar SoC, temperature, and power patterns. It provides an intuitive benchmark for comparison with complex models. This method uses clustering techniques such as K-means or DBSCAN to identify natural groupings in the data. It simplifies the evaluation process by offering clear and interpretable group-level behaviour. Moreover, it helps highlight anomalies or outliers in charging behavior that may require further investigation.

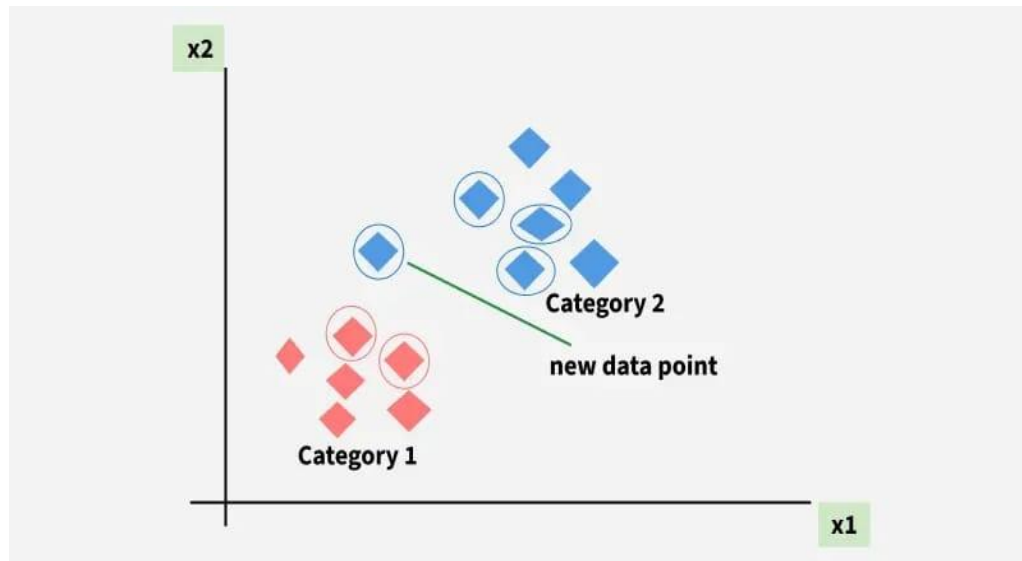


Fig 1: K-Nearest Neighbours (KNN) algorithm

Charging Stage Identification Algorithm (Power Gradient-Based):

Detects charging phases such as Constant Current (CC), Constant Voltage (CV), and End-of-Charge (EOC) from power data. This enhances feature quality by providing stage-aware input to the classifier. By segmenting the charging session into distinct phases, the model gains a better understanding of battery behavior over time. These phase-specific features improve classification accuracy by aligning model inputs with known electrochemical charging patterns.

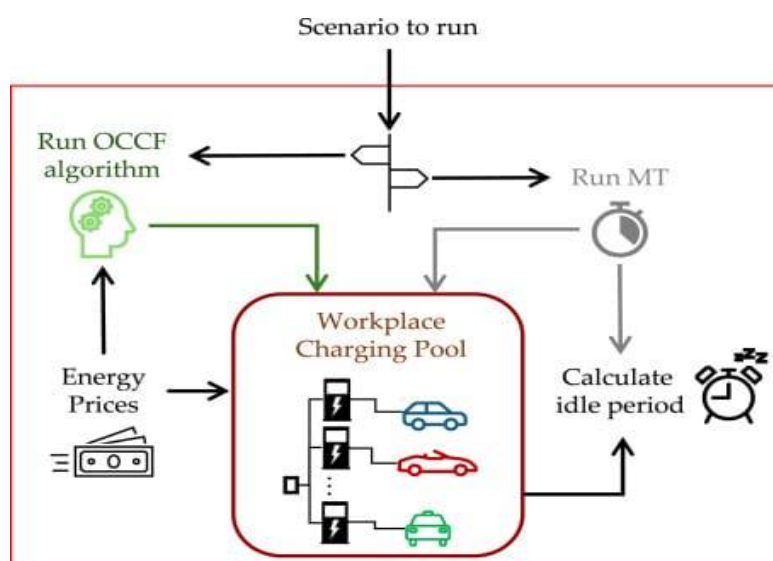


Fig 2: Optimal Charging Coordination Framework (OCCF) for Electric Vehicle (EV) Workplace Charging Management.

Multi-Objective Particle Swarm Optimization (MOPSO):

Once the classifier predicts the optimal charging class, MOPSO is applied to balance multiple objectives—such as minimizing battery wear, energy cost, and charging time—by generating Pareto-optimal solutions.

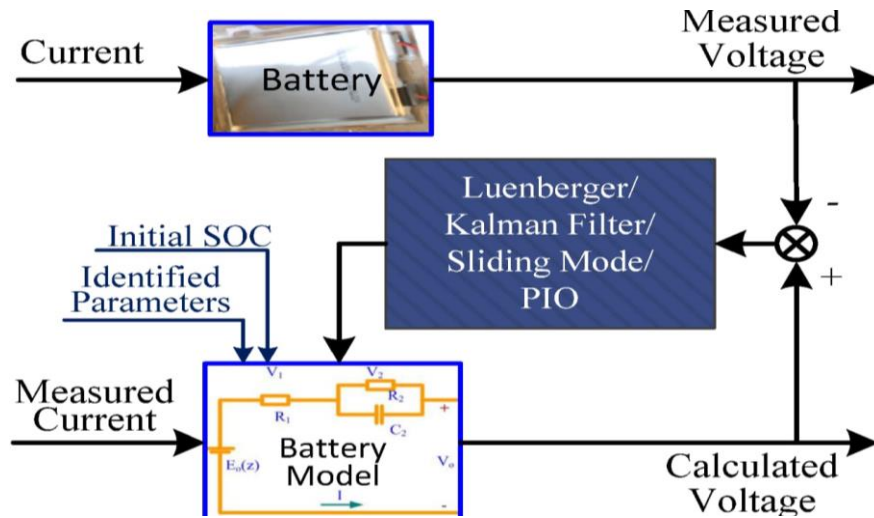


Fig 3: Battery State of Charge (SOC) Estimation System

AHP+TOPSIS (Hybrid Multi-Criteria Decision-Making):

These decision-making algorithms are used to rank the optimal solutions generated by MOPSO. AHP assigns priority weights to criteria (like cost, battery health, and user convenience), while TOPSIS selects the best trade-off solution close to the ideal one.

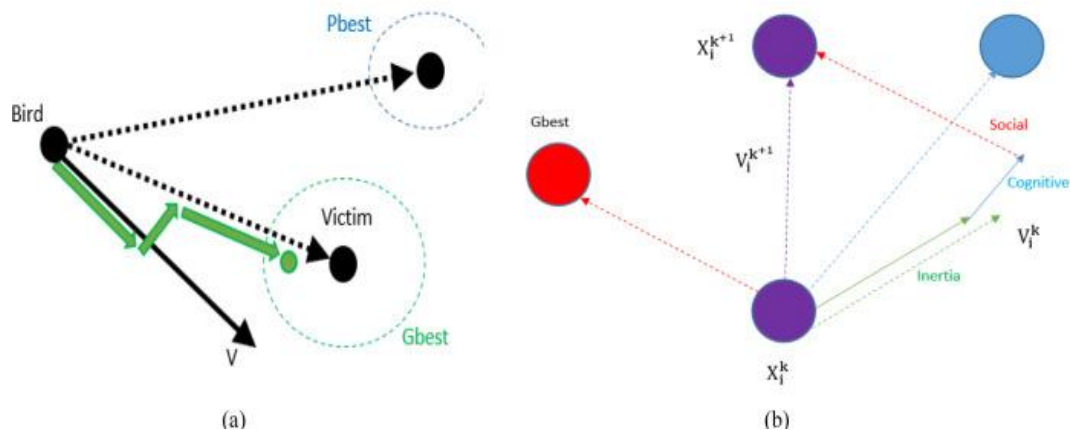


Fig 4: Particle Swarm Optimization (PSO) algorithm.

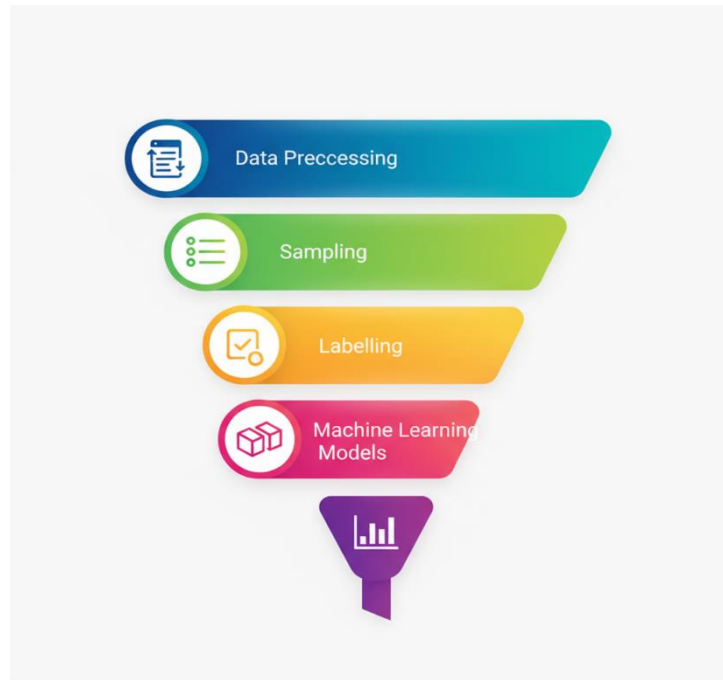
Output Stage

The output stage translates model predictions and optimizations into actionable charging recommendations.

The results are delivered through a smart adaptive charging scheduler, which suggests personalized charging durations and power levels based on user patterns, grid status, and battery conditions.

The final system outputs include:

- Recommended charging duration and mode (Fast, Balanced, or Trickle).
- Predicted SoC trajectory over the charging session.
- Alerts for overheating or degradation risks.
- Optimized schedules that minimize cost and energy loss.
- This integration of machine learning and optimization enables adaptive, reliable, and energy-efficient EV charging management.

BLOCK DIAGRAM:**Fig 5: Data Science Workflow Funnel**

- **Input Layer:** Collects real-time data from the Battery Management System (BMS), charger, and surrounding environment, including parameters such as State of Charge (SoC), voltage, current, temperature, and ambient conditions.
- **Preprocessing Layer:** Cleans, filters, and standardizes raw input data to ensure consistency and reliability. This involves noise reduction, handling of missing or outlier values, normalization of features.
- **Classification Layer:** Employs machine learning algorithms such as K-Nearest Neighbors (KNN), Random Forest (RF), and Support Vector Machines (SVM) to classify charging sessions based on patterns in the input features.
- **Optimization Layer:** Applies multi-objective optimization techniques such as Multi-Objective Particle Swarm Optimization (MOPSO), Analytic Hierarchy Process (AHP), and Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS). These are used to evaluate and balance conflicting objectives like minimizing charging time and cost while maximizing battery health and efficiency.
- **Output Layer:** Generates actionable outputs including optimal charging recommendations tailored to the vehicle and usage context, real-time risk alerts for unsafe charging behaviors, and adaptive scheduling suggestions. It can interface with the EV charging station, user apps, or fleet management systems to implement intelligent control and monitoring

CONCLUSION:

The results of this study emphasize that combining classification and optimization techniques can significantly improve EV charging efficiency and battery longevity. The machine learning models can adapt to real-time operational data, enabling intelligent scheduling that reduces overcharging risks and ensures energy-efficient charging. Moreover, the adaptive nature of the proposed framework supports scalability for large-scale deployment in public or home charging networks.

In conclusion, the machine learning-driven classification for optimized EV battery charging provides a powerful and practical solution for managing the complexities of modern electric vehicle ecosystems. It bridges the gap between battery science, data analytics, and real-time decision-making. Future work can focus on incorporating real-time grid data, dynamic tariff adjustments.

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