Predictive Modeling of Electric Vehicle Charging Duration Using Multilayer Perceptron Neural Networks

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DOI: https://doi.org/10.51244/IJRSI.2026.1303000195

Received: 27 March 2026; Accepted: 01 April 2026; Published: 14 April 2026

ABSTRACT

Accurate prediction of electric vehicle (EV) charging duration is essential for efficient energy management and enhanced user experience. However, variability in charging patterns, battery conditions, and operational factors makes reliable prediction challenging. While charging duration is inherently continuous, practical EV charging operations often require approximate duration ranges rather than exact times. Therefore, this study reformulates the prediction task as a classification problem by discretizing charging duration into predefined categories.

A Multilayer Perceptron Neural Network (MLPN) is employed to classify EV charging durations as Low or Long. The model is trained on a real-world dataset containing 2,000 charging sessions, with relevant features such as energy consumed and temporal attributes derived from charging start times. Preprocessing steps, including normalization and feature selection, are applied to enhance model accuracy.

Two optimization algorithms, Stochastic Gradient Descent (SGD) and Adaptive Moment Estimation (Adam) are evaluated for their impact on model performance. Classification metrics including accuracy, precision, recall, and F1-score are used for evaluation. The results indicate that the MLPN model accurately classifies charging duration, with SGD achieving superior performance. The proposed approach provides a practical data-driven solution for EV charging duration prediction, supporting efficient energy utilization and improved operational planning.

Keywords: MLPN, Electric Vehicle, Charging Duration Classification, SGD, Adam Optimizer, Feature Engineering

INTRODUCTION

The rapid adoption of electric vehicles (EVs) has increased demand for intelligent charging infrastructure. One critical challenge is accurately predicting charging duration, as it directly influences user satisfaction, energy planning, and charging station efficiency. Variability in battery state, charging power, user behavior, and environmental factors makes exact duration prediction difficult.

Traditional approaches often estimate continuous charging times, but in practice, approximate duration ranges are more actionable for scheduling and operational planning. This motivates treating charging duration as a classification problem, where sessions are grouped into categories (e.g., Low and Long) to facilitate practical decision-making.

Machine learning (ML), particularly Artificial Neural Networks (ANNs), has proven effective in modeling non-linear relationships in data. Among ANNs, Multilayer Perceptron Neural Networks (MLPN) can learn complex patterns in EV charging data, making them suitable for classification tasks. Additionally, optimization algorithms such as SGD and Adam enhance model training efficiency and predictive accuracy.

ISSN No. 2321-2705 | DOI: 10.51244/IJRSI |Volume XIII Issue III March 2026

This study develops an MLPN-based classification model for EV charging duration, using a real-world dataset and comparing the effectiveness of SGD and Adam optimizers. The goal is to provide a robust, data-driven solution for practical EV charging duration estimation.

Related Works

Recent studies have explored the application of machine learning techniques in predicting electric vehicle (EV) charging behavior, including charging duration, energy consumption, and user patterns. Accurate prediction of charging duration remains a critical challenge due to variability in user behavior, battery conditions, and environmental factors.

Majidpour et al. (2014) applied machine learning algorithms such as Support Vector Machine (SVM), Random Forest (RF), and Modified Pattern-Based Sequence Forecasting (MPSF) to predict charging outlet usage and energy consumption. Their findings indicated that MPSF outperformed other models, achieving a SMAPE of 14.06%. However, the study focused more on energy consumption than charging duration prediction.

Khaki et al. (2019) developed an ensemble model combining Artificial Neural Networks (ANN), SVM, and Decision Trees (DT) to predict EV charging behavior using UK household data. The model successfully predicted charging duration and energy usage, but its performance was limited by insufficient data generalization.

Xiong et al. (2019) utilized a Linear Regression (LR) model to predict EV user behavior, including session duration and start time. Although effective, the model lacked the ability to capture complex nonlinear relationships inherent in EV charging data.

Chung et al. (2019) employed machine learning techniques such as RF, K-Nearest Neighbor (KNN), and SVM to predict charging session duration and energy consumption. Their results showed that SVM performed best for duration prediction, while RF was more effective for energy estimation. However, the study did not explore deep learning models for improved performance.

Shahriar et al. (2021) proposed a hybrid machine learning approach incorporating RF, SVM, XGBoost, and ANN to predict charging session duration and energy consumption. The inclusion of additional contextual data improved prediction accuracy, although the model's performance was sensitive to data variability.

Xu (2019) applied SVM to estimate EV arrival and departure times, achieving low mean absolute error. However, the study did not directly address charging duration prediction.

Liu et al. (2022) focused on machine learning techniques for battery degradation prediction and energy management in EV systems. While their approach improved battery lifespan, it did not directly address charging duration prediction.

Despite these advancements, most existing studies either focus on energy consumption, charging behavior, or battery management, with limited emphasis on accurate prediction of charging duration using deep learning approaches. Furthermore, few studies have explored the comparative impact of optimization algorithms on neural network performance in this domain.

This study addresses these gaps by developing a predictive model based on a Multilayer Perceptron Neural Network (MLPN) to estimate EV charging duration. Additionally, the performance of Stochastic Gradient Descent (SGD) and Adaptive Moment Estimation (Adam) optimizers is evaluated to enhance prediction accuracy.

Machine Learning:

Machine learning, as a data analytics technique, teaches computers to learn from experience using computational methods to derive insights directly from data without relying on predetermined equations. This approach enables machines to acquire or modify knowledge, behaviors, values, and skills. Coined by Arthur

Samuel in 1959, machine learning is defined as a field that provides learning capability to computers without explicit programming. Machine learning applications span various areas of computing, enabling the design and programming of high-performance algorithms. These applications include email spam filtering, fraud detection, online stock trading, face and shape detection, medical diagnosis, and traffic prediction. Cross-entropy, a fundamental metric in classification tasks, plays a pivotal role in evaluating machine learning models by comparing predictions with actual labels, providing insights into accuracy and generalizability. "In areas where electricity is rare, charging stations, which are frequently fueled by a variety of energy sources, including solar energy systems, generators, or even portable battery packs, provides a solution.

Types of Machine Learning Algorithms

The main types of ML algorithms include **supervised learning, unsupervised learning, semi-supervised learning, and reinforcement learning** (Ding et al., 2020).

Supervised Learning

Supervised learning trains a model using a **labeled dataset**, where each input is paired with an output label. The model infers a mapping function f(x)f(x)f(x) from the training data to predict outcomes for unseen instances (Bae et al., 2019). The dataset is divided into a **training set**, containing input-output pairs, and a **test set**, which contains only input patterns. During training, the algorithm identifies patterns in the input features and learns to map them to the corresponding output classes. The main goal is to construct a model capable of accurately classifying or predicting new data. While effective, supervised learning often requires **large amounts of labeled data**, making it a time-consuming and resource-intensive process. By building a knowledge base from pre-classified patterns, the model can generalize to classify previously unseen instances.

Unsupervised Learning

Unsupervised learning trains models on **unlabeled data** to discover patterns and structures without human supervision (Caron et al., 2018). Unlike supervised learning, it does not require explicit target outputs. Common techniques include **clustering (k-means, hierarchical), PCA, ICA, SVD, EM**, and density estimation methods. While unsupervised learning can yield unexpected insights and supports deep learning development (Krotov & Hopfield, 2019), it may struggle to accurately cluster unknown data. It is widely applied in **machine vision, speech recognition, self-driving cars, natural language processing, and anomaly detection** (Mirnaghi & Haghighat, 2020).

Semi-Supervised Learning

Semi-supervised learning (SSL) combines a **small labeled dataset with a large unlabeled dataset** to improve learning efficiency (Methani et al., 2012; Mohammed et al., 2016). It is particularly useful when labeling data is expensive or time-consuming, for example in **image or text classification**. SSL algorithms rely on assumptions such as **smoothness** or **low-density regions** to make predictions more robust (Rasmus et al., 2015; Laine & Aila, 2017; Tarvainen & Valpola, 2017).

Reinforcement Learning

Reinforcement learning (RL) involves an **agent interacting with an environment** to maximize cumulative rewards through trial and error (Sutton & Barto, 1998, 2018; Bertsekas & Tsitsiklis, 1996). The integration with deep neural networks has led to **deep reinforcement learning**, widely used in **game playing (e.g., AlphaGo), robotics, and autonomous driving** (LeCun et al., 2015; Goodfellow et al., 2016; Schmidhuber, 2015). Key algorithms include **Q-Learning, Deep Q-Networks (DQN), and Policy Gradient Methods**.

INTERNATIONAL JOURNAL OF RESEARCH AND SCIENTIFIC INNOVATION (IJRSI)
ISSN No. 2321-2705 | DOI: 10.51244/IJRSI |Volume XIII Issue III March 2026

MATERIALS AND METHODS

Dataset Description

(a) Sample dataset: This shows the EV charging dataset as retrieved from the kaggle site(Source: "https://data.cityofpaloalto.org/dataviews/257812/ELECT-VEHIC-CHARG-STATI-83602/"). It comprises of file 1 as the raw data stored in excel CSV format. The dataset undergoes what is called data pre-processing.

(b) Table 1: Dataset for EV**(source:** https://data.cityofpaloalto.org/dataviews/257812/ELECT-VEHIC-CHARG-STATI-83602/"**)**

Station Name	Start Date	End Date	Transaction Date (Pacific Time)	Total Duration (hh:mm:ss)	Charging Time (hh:mm:ss)	Energy (kWh)	Gasoline Savings (gallons)	Latitude	Longitude	Driver Postal Code	User ID
PALO ALTO CA / HAMILTON #1	7/29/2011 20:17	7/29/2011 23:20	7/29/2011 23:20	3:03:32	1:54:03	6.2494u57	0.784	37.444572	-122.160309	95124	3284
PALO ALTO CA / HAMILTON #1	7/30/2011 0:00	7/30/2011 0:02	7/30/2011 0:02	0:02:06	0:01:54	0.106588	0.013	37.444572	-122.160309	94301	4169
PALO ALTO CA / HAMILTON #1	7/30/2011 8:16	7/30/2011 12:34	7/30/2011 12:34	4:17:32	4:17:28	14.951777	1.876	37.444572	-122.160309	94301	4169
PALO ALTO CA / HAMILTON #1	7/30/2011 14:51	7/30/2011 16:55	7/30/2011 16:55	2:03:24	2:02:58	7.159643	0.899	37.444572	-122.160309	94302	2545
PALO ALTO CA / HAMILTON #1	7/30/2011 18:51	7/30/2011 20:03	7/30/2011 20:03	1:11:24	0:43:54	1.957765	0.246	37.444572	-122.160309	94043	3765

(c) EV Dataset

(c)The dataset contains **2,000 EV charging session records** collected from Palo Alto charging stations. Each session includes features such as:

- **Charging Time (hh:mm:ss)** – Target variable (discretized for classification)
- **Energy (kWh)** – Amount of energy delivered
- **Temporal Features** – Hour of day, day of week (derived from Start Date)

Charging duration was **discretized into categories**:

ISSN No. 2321-2705 | DOI: 10.51244/IJRSI |Volume XIII Issue III March 2026

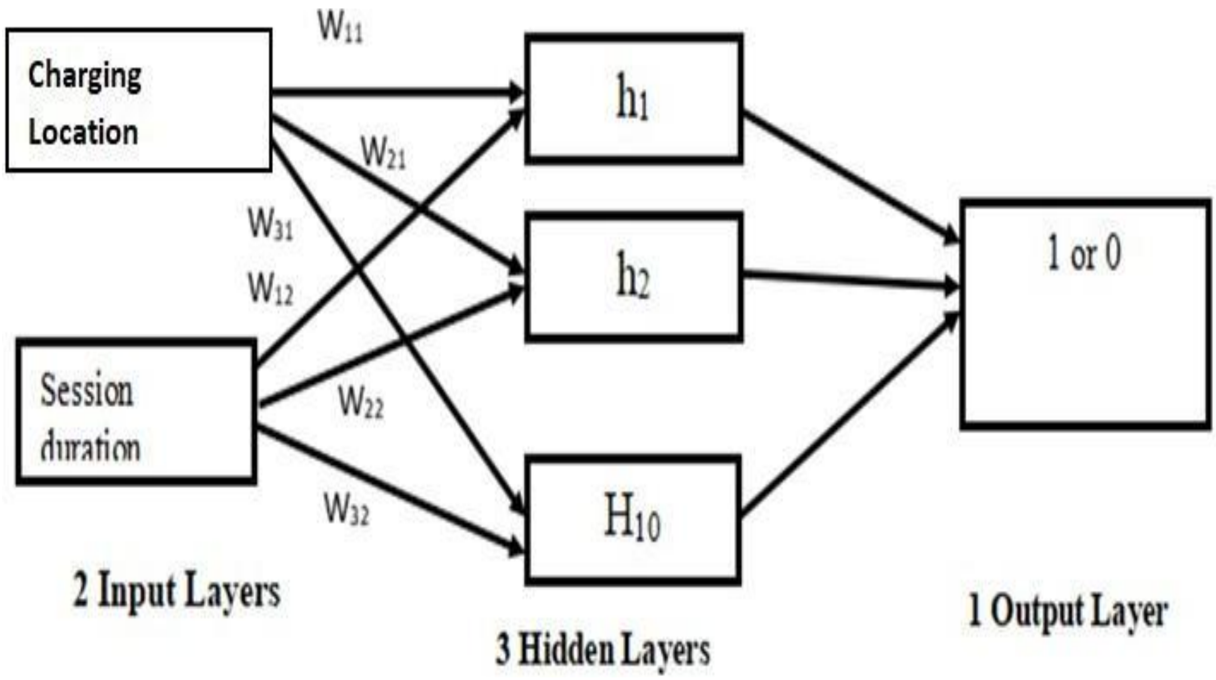
- **Low:** 0–90 minutes
- **Long:** >90 minutes

This categorization reflects real-world operational needs where approximate ranges guide scheduling and resource allocation.

Data Preprocessing

- **Normalization:** Features scaled to 0–1 range using Min-Max scaling.
- **Feature Engineering:** Temporal attributes derived from timestamps to capture patterns.
- **Data Cleaning:** Corrected inconsistent values (e.g., energy readings) and ensured no missing values.

Model Architecture



The MLPN model consists of:

- Input layer: accepts normalized features
- Hidden layers: captures non-linear patterns
- Output layer: two nodes for Low and Long classes

Training and Optimization

The model was trained using:

1. **Stochastic Gradient Descent (SGD):** iterative weight updates using small batches to minimize cross-entropy loss.
2. **Adaptive Moment Estimation (Adam):** combines momentum and adaptive learning rates for efficient convergence.

INTERNATIONAL JOURNAL OF RESEARCH AND SCIENTIFIC INNOVATION (IJRSI)
ISSN No. 2321-2705 | DOI: 10.51244/IJRSI |Volume XIII Issue III March 2026

Dataset Split: 70% training, 30% testing.

Training and Validation Performance of MLPN Model”.

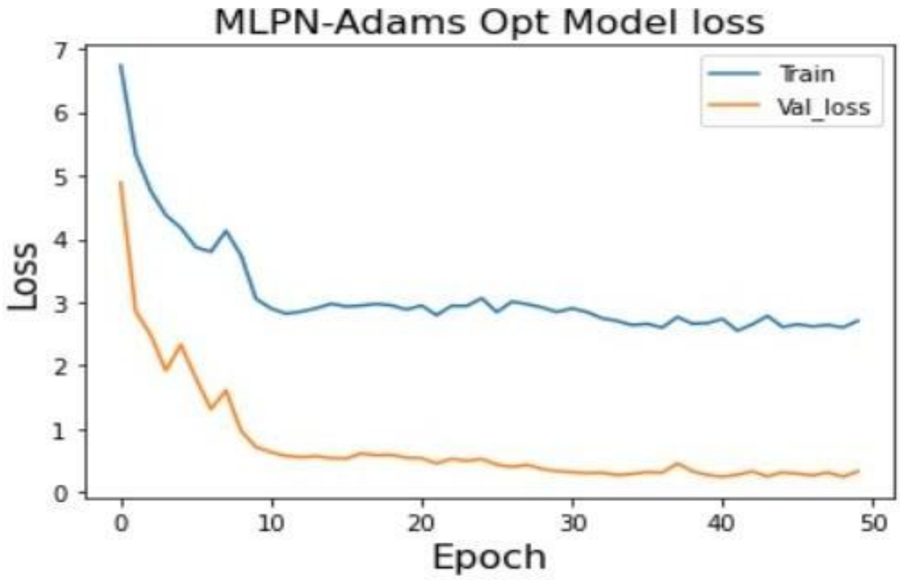


Figure 1: Training and Validation Loss (MLPN–Adam Optimization)

The training and validation loss curves presented in Figure 1 provide insight into the learning behavior of the MLPN model over 50 epochs. The gradual decrease in both training and validation loss indicates that the model effectively learns patterns from the dataset.

The close alignment between the training and validation curves suggests good generalization performance with minimal overfitting.

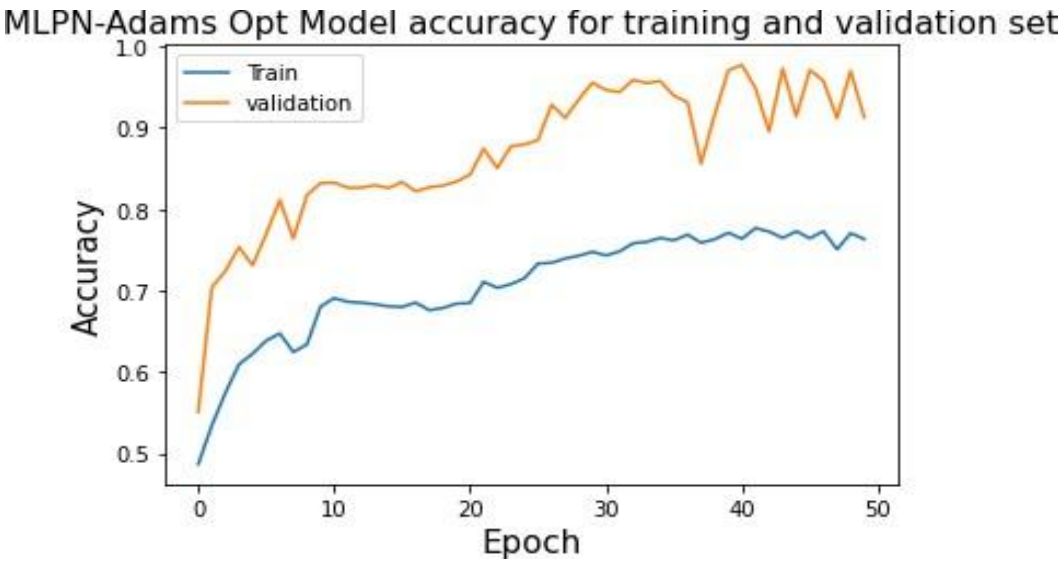


Figure 2: Training and Validation Loss Behavior

Figure 2 illustrates the variation in training and validation loss during model training. At the initial stage, the validation loss increases slightly, indicating temporary instability in learning. However, as training progresses beyond approximately 25 epochs, the validation loss begins to decrease and stabilizes. This behavior suggests that the model initially experiences slight overfitting but gradually improves its generalization capability. The fluctuation observed in the validation curve indicates sensitivity to data variation, which is common in neural network training. To mitigate overfitting, techniques such as early stopping can be applied by terminating training when validation loss begins to increase consistently.

Performance Evaluation (Test Results)

Table 1. Classification Report – MLPN-Adam Optimizer

Class	Precision	Recall	F1-Score	Support
Low	1.00	0.84	0.92	354
Long	0.97	1.00	0.98	1646
Accuracy	-	-	0.93	2000
Macro Avg	0.98	0.92	0.95	2000
Weighted Avg	0.97	0.97	0.97	2000

Table 2. Classification Report – MLPN-SGD Optimizer

Class	Precision	Recall	F1-Score	Support
Low	0.72	1.00	0.84	354
Long	1.00	0.92	0.96	1646
Accuracy	-	-	0.93	2000
Macro Avg	0.86	0.96	0.90	2000
Weighted Avg	0.95	0.93	0.94	2000

Summary of Results

Both MLPN models achieved an overall accuracy of **93%**, indicating strong predictive performance. The **Adam optimizer** performed better in predicting the *Long* class with higher recall and F1-score, while the **SGD optimizer** was more effective in identifying the *Low* class but with reduced precision. Overall, Adam provided more balanced performance, whereas SGD showed a trade-off between recall and precision.

The results demonstrate that the MLPNN model is effective for predicting charging duration categories, thereby supporting intelligent decision-making in electric vehicle charging station management.

CONCLUSION

This study presents a predictive modeling approach for estimating electric vehicle (EV) charging duration using a Multilayer Perceptron Neural Network (MLPN). Accurate prediction of charging duration is essential for improving energy planning, enhancing user experience, and supporting efficient operation of EV charging systems. The proposed model was developed using supervised machine learning techniques and trained on a real-world dataset. To enhance learning performance, Stochastic Gradient Descent (SGD) and Adaptive Moment Estimation (Adam) optimizers were employed and comparatively evaluated. The results demonstrate that the MLPN model effectively captures the underlying patterns in EV charging data and provides accurate predictions of charging duration. Furthermore, the findings indicate that the choice of optimization algorithm significantly influences model performance, with SGD showing improved results in terms of accuracy and classification metrics. The integration of feature engineering and data preprocessing techniques also contributed to enhancing the model's predictive capability. Overall, this study highlights the effectiveness of machine learning approaches, particularly MLPN, in predicting EV charging duration. The proposed model provides a reliable data-driven solution that can support better decision-making in EV charging systems and contribute to improved efficiency in energy utilization.

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