Certain Investigations on AI/ML Applications in Electric Vehicles

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[1] Abstract—This study delves into the dynamic landscape of AI/ML applications within the realm of Electric Vehicles (EVs). It encompasses a comprehensive analysis of methodologies, including CNNs for battery lifetime prediction, ML for accurate range forecasting, optimization of EV charge scheduling through ML techniques, and precise state-of-charge (SOC) estimation via machine learning algorithms. Furthermore, AI's role extends to load forecasting at EV charging stations, while ML models play a pivotal role in anticipating intricate EV charging behaviors.

Abbreviations
Electrical Vehicle – EV
Machine Learning – ML
Artificial Intelligence – AI
Convolutional Neural Networks – CNN
Absolute Mean Error – MAE
Mean Absolute Percentage Error – MAPE
Relative Error – RE
Root Mean Squared Error – RMSE
State Of Charge – SOC
Support Vector Machine – SVM
Vehicle to Grid – V2G

INTRODUCTION

The infusion of Artificial Intelligence (AI) and Machine Learning (ML) into Electric Vehicle (EV) applications is reshaping predictive analysis and future trends. AI's exponential growth has positioned it as a central player in predictive methodologies, set to profoundly influence the automotive landscape.

One striking application is the prediction of EV battery life. AI, powered by ML algorithms, dissects driving patterns, temperature fluctuations, battery usage, and charging routines to craft precise predictive models. These models gain precision as they incorporate larger EV datasets and historical insights.

Real-time battery monitoring and early degradation detection showcase AI's vigilance. Anticipating battery replacements optimizes efficiency and cost-effectiveness. Additionally, AI fine-tunes EV charging strategies by considering station availability, electricity costs, and travel expectations, elongating battery lifespan and minimizing replacements.

AI's influence extends to elevating overall EV battery efficiency. Through AI-powered predictive models and charging optimization, the aim is to enhance consumer access and satisfaction. This fusion revolutionizes EV charging stations and behavior, making them more appealing, user-driven, and environmentally conscious.

Battery Lifetime prediction of electrical vehicle using CNNs

Anticipating battery lifespan through charging cycles is a significant recent investigation. Enhanced predictions aid quality assessment and EV long-term planning.

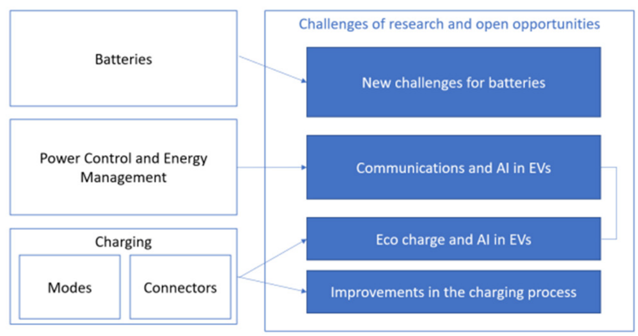

Fig. 1. Application of AI in EV

Predicting cumulative cycles and failure points is crucial. Can the battery endure more cycles before failing?

Our goal is to predict the battery's age and remaining life using limited charge cycle data.

Using 124 lithium-ion cells, this study collected data. Cells underwent charging, discharging until 'broken.' Cycle count to failure is battery cycle life.

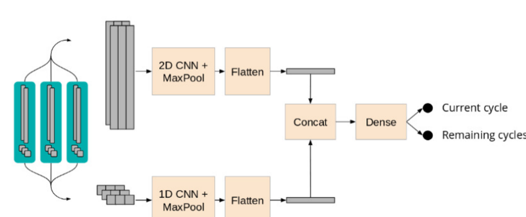

Fig. 2. Implementation of CNNs in Electrical vehicles.

Complete cycle data included time-based attributes: capacity, temperature, voltage, current. Scalar traits like

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internal resistance, cycle time were also noted.

Convolutional Neural Networks (CNNs) in TensorFlow and Keras predicted target variables.

Data fed in the model is two types: array and scalar features. Processed separately, then merged. Data is fed through a dense network, generating outputs. This approach handles diverse input, provides accurate predictions.

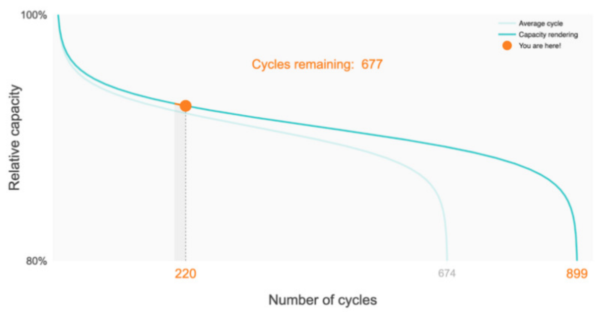

Fig. 3. Result in the graph Implementation of CNNs in EV

Graph clearly shows accurate predictions for battery age, expected lifetime. Data suggests battery lifetime: around 900 cycles, current age: around 220 cycles, implying 677 remaining cycles. This model fits various battery datasets similarly."

Range prediction for EV using ML

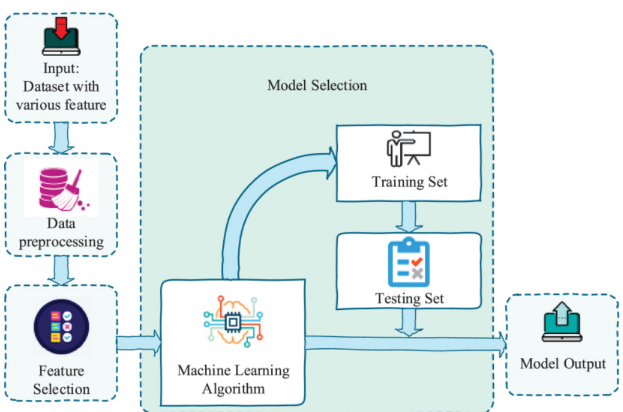

Fig. 4. Overview of range prediction process using ML

The limited driving range is a key obstacle to wider electric vehicle (EV) adoption. To address this, a hybrid machine learning model is proposed in this study. It uses real-world driving data to accurately predict remaining travel distance, alleviating range anxiety and boosting EV driver confidence.

The model is trained on diverse factors including motor and battery energy, driving behavior, and temperature. The initial phase focuses on algorithm training using a dataset of over two thousand trips, covering 600,000+ kilometers with five identical-model EVs.

After feature selection, the machine learning model predicts remaining range based on State Of Charge (SOC). Model performance is evaluated using metrics like MAE, RMSE, and MAPE.

This research introduces an innovative approach to forecast EV travel distance based on SOC, improving usability and driver confidence.

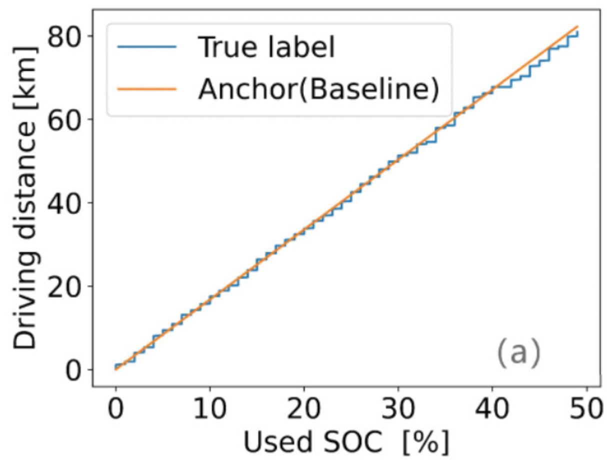

Fig. 5. Result in the graph range prediction

Besides the State Of Charge (SOC), the machine learning model incorporates various other features like fast charging capacity, efficiency, top speed, and acceleration of the vehicle. These additions substantially enhance the predictive accuracy of the model. By utilizing a broader dataset, the model gains the ability to provide more accurate and dependable forecasts regarding the electric vehicle's remaining driving range.

Electric vehicle charge scheduling using machine learning

This research employs Support Vector Machine (SVM) to analyze home charge scheduling and determine an electric vehicle's status: idle, Grid to Vehicle (G2V) charging, or Vehicle to Grid (V2G) charging. The SVM model uses user energy consumption and State of Charge (SOC) data at different time segments to predict the vehicle's status with almost 100% accuracy.

The SVM model is trained using six days' worth of data at 30-minute intervals, including power consumption, trip duration, and SOC. The output data is labeled: Idle (1), G2V (2), and V2G (3). By establishing decision boundaries for each class, the SVM accurately identifies the vehicle's status based on the input features.

This approach relies on smart meter readings and SOC to determine whether the vehicle is idle, in G2V charging, or V2G charging. SVM's decision boundaries define the vehicle's state.

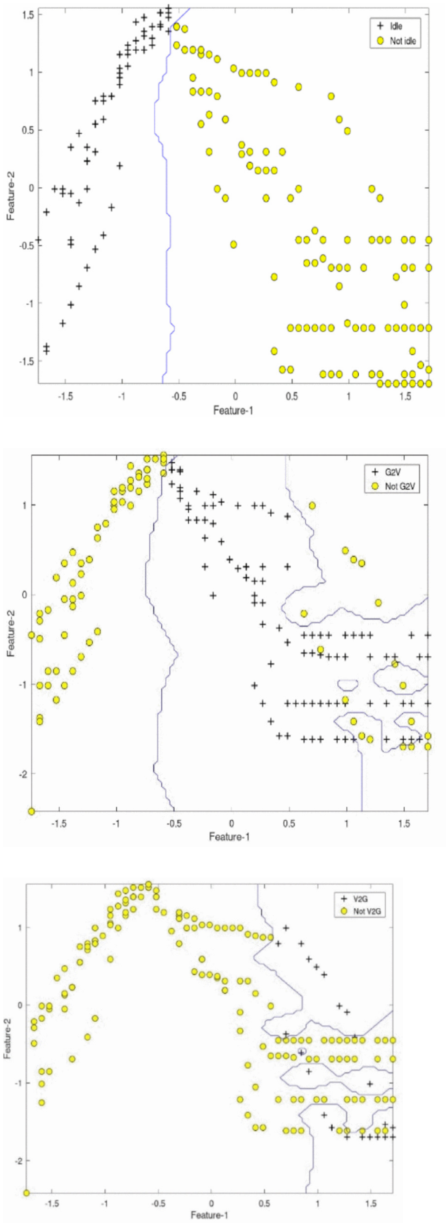

Fig. 6. Result of charging schedule

After partitioning the complete dataset into three subsets, individual analyses were conducted for each labeled output. To ensure consistency, all features were normalized to a common scale.

Decision boundaries were visualized for three scenarios: Idle, G2V, and V2G. A detailed performance analysis was carried out for each case. In this context, "feature-1" represents State of Charge (SOC) data from the vehicle owner, while "feature-2" corresponds to energy consumption values measured by the smart meter. Due to normalization, specific units for these features were not provided.

In the visualizations, the blue line signifies the decision boundary. The trained model accurately classified the two examples, underscoring its effectiveness in making reliable predictions for the output classes (Idle, G2V, and V2G).

ML based SOC estimation of electric vehicles

This study introduces an SOC estimation model using ML algorithms, leveraging driving data from EVs. Through experiments with various ML algorithms, the model accurately estimates EVs' SOC status during motion.

Creating an ML-based SOC estimation model requires substantial charge/discharge data, which is challenging due to SOC's nonlinearity. Experimental data might not fully represent SOC variations under different drivers, differing from real driving conditions.

To overcome this, a novel SOC estimation approach is proposed, using extensive cloud-stored driving data. This method analyzes real-world driving patterns of multiple EVs, leading to more reliable predictions, complementing limited experimental data.

Time	Speed (Km/H)	Mileage (Km)	Lon	Lat	SOC
16/04/2018 04:24:52	0	43173	116.68	39.88	76
16/04/2018 04:25:02	0	43173	116.68	39.88	76
16/04/2018 04:25:12	0	43173	116.68	39.88	76
16/04/2018 04:25:22	0	43173	116.68	39.88	76
16/04/2018 04:25:33	0.6	43173	116.68	39.88	76
16/04/2018 00:00:00	3.2	43173	116.68	39.88	76
16/04/2018 04:26:23	19.7	432173	116.68	39.88	76
16/04/2018 04:26:33	0.9	43173	116.68	39.88	75

Table. 1. Data used for analysis

This study gathers driving data from different EVs of the same model, comprising records from 5 EVs across a year, totaling approximately one million cleaned records. Data is captured every 10 seconds during EV operation.

Various prominent ML algorithms are chosen to build the SOC estimation model. Model effectiveness is assessed using two performance metrics: Mean Absolute Error (MAE) and Relative Error (RE).

The SOC estimation models are constructed with different ML algorithms and evaluated using MAE and RE. Additionally, the model's predictive abilities across time intervals – half an hour, one hour, and two hours of EV driving – are examined, offering insights into its performance over varying durations.

Model	Forecast (Hours)	MAE	MAE Variance	RE
SI_LGB	0.5	0.880	0.827	0.026
	1.0	1.446	2.206	0.042
	2.0	2.379	5.773	0.066
SI_GBDT	0.5	0.897	0.931	0.027
	1.0	1.493	2.644	0.044
	2.0	2.492	7.500	0.071
SI_BPNN	0.5	1.312	2.073	0.046
	1.0	2.312	5.979	0.080
	2.0	4.011	16.382	0.129
SI_ElasticNet	0.5	1.302	1.668	0.042
	1.0	2.210	4.490	0.070
	2.0	3.691	11.331	0.111
DA_RF	0.5	0.776	5.879	0.065
	1.0	1.499	16.991	0.109
	0.2	2.930	49.208	0.178
DA_LGB	0.5	0.975	7.755	0.058
	1.0	1.673	23.143	0.095
	2.0	2.909	69.937	0.170

Table. 2. Result of SOC estimation of electric vehicle

This study introduces a method to estimate the State of Charge (SOC) of electric vehicles (EVs) using limited data. The model uses fewer inputs while maintaining similar SOC estimation accuracy to algorithms based on complex power battery models. This discovery is significant as it simplifies EV travel planning, requiring less data and making SOC estimation more practical in real-world scenarios. This approach empowers EV users and planners to make informed travel decisions, optimizing energy use and improving overall efficiency.

Forecasting the load of electric vehicle charging station using AI [8]

With the rapid rise of electric vehicles (EVs), power grids face fresh challenges as load profiles undergo significant shifts. To tackle this, a novel approach is introduced in this study, utilizing machine learning (ML) techniques to predict loads on EV charging stations. By precisely forecasting these loads, the approach aims to help power grids efficiently manage resources and accommodate the growing EV demand.

As electric vehicle adoption continues to expand, energy management within power grids grows more intricate and demanding. This complexity arises primarily from EVs' influence on market prices and electricity requirements. As a result, accurate forecasting of EV charging load demand becomes crucial for effective power grid management.

This research compares three widely recognized artificial intelligence (AI) techniques - Artificial Neural Network (ANN), Recurrent Neural Network (RNN), and Q-learning - for EV charging load prediction [8]. The goal is to showcase the merits and efficacy of these ML techniques across diverse scenarios.

For all three methods, the input consists of 24 data points, representing the past 24 hours, used to predict the charging load for the upcoming hour. In ANN and RNN, the input and output units involve previous EV load data.

The Q-learning technique [8] leverages predictions from ANN and RNN for preceding days. Experimental outcomes are presented in Figure 7, illustrating AI-driven forecasts for EV charging stations.

Results suggest that the Q-learning technique, which integrates information from both ANN and RNN, surpasses them in accurately predicting EV load charging. Simulations indicate that Q-learning achieves more precise load forecasts for EVs compared to ANN and RNN techniques.

In summary, the proposed Q-learning technique excels in faster, more accurate, and flexible tracking of EV load, surpassing the capabilities of ANN and RNN techniques. Furthermore, varying hidden layer numbers, epoch numbers (iterations), and node numbers can notably enhance the accuracy of EV charging load forecasting. [8]

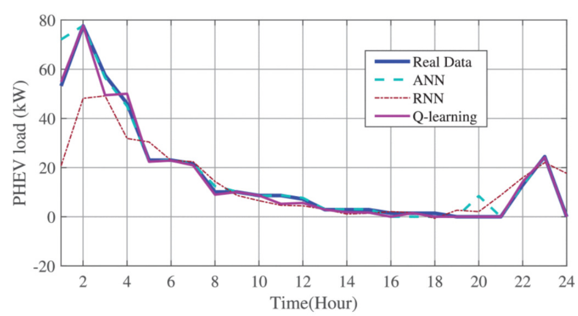

Fig. 7. Result – forecast of EV charging station using AI

Prediction of EV charging behavior using ML

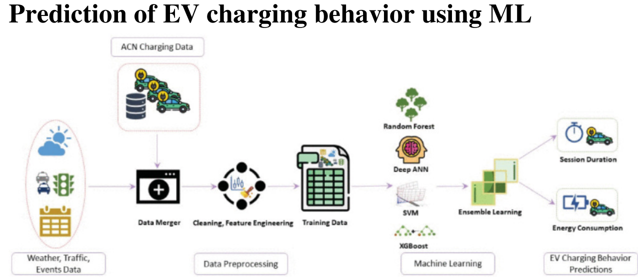

Fig. 8. [9] Overview of the implementation

The rapid adoption of electric vehicles (EVs) presents a notable challenge to power grid infrastructure. To tackle this, intelligent scheduling algorithms can effectively manage the surging demand for public charging. Leveraging data-driven tools and machine learning (ML) algorithms to comprehend EV charging behavior can further enhance these scheduling strategies.

This study introduces a method that merges historical charging data with weather, traffic, and events data to forecast both EV session duration and energy consumption [9]. These essential factors are targeted for prediction using various ML techniques.

The innovative approach proposed here employs weather, traffic, and local events data in conjunction with historical charging records to forecast EV charging behavior [9]. Multiple ML algorithms, including RF, SVM, XGBoost, and ANN, are applied to the adaptive charging network (ACN) dataset [9].

Empirical findings underscore the positive impact of incorporating additional data on prediction accuracy [9], outperforming previous methods reliant solely on historical charging information. This approach notably enhances the understanding and prediction of EV charging behavior [9], ultimately optimizing charging networks and addressing the challenges associated with the widespread deployment of EVs.

Metrics / Model	RMSE (kWh)	MAE (kWh)	R^2	SMAPE (%)
RF	98.7	68	0.63	10.1
SVM	101	67.4	0.64	10.1
XGBoost	97.9	68	0.63	10.1
Deep ANN	101	73.7	0.57	10.9
Voting Ensemble	97.7	66.5	0.73	9.92
Stacking Ensemble	97.5	67.1	0.73	9.95
User predictions	430	394	-4.20	69.9

Table. 3 [9] Session Duration

Metrics / Model	RMSE (kWh)	MAE (kWh)	R^2	SMAPE (%)
RF	5.5	3.39	0.54	11.7
SVM	5.69	3.54	0.51	12.4
XGBoost	5.61	3.48	0.51	12.1
Deep ANN	5.65	3.55	0.55	12.5
Voting Ensemble	5.54	3.41	0.69	11.8
Stacking Ensemble	5.5	3.38	0.70	11.6
User predictions	20.6	11.8	0.04	55.0

Table. 4 [9] Energy Consumption

The study identifies the most critical predictors for session duration: maximum traffic post-arrival and connection time. This underscores the importance of integrating traffic data for precise duration predictions [9].

For energy consumption, historical average usage emerges as the key factor. This is due to a consistent energy consumption pattern when session duration remains unchanged.

The evaluation of developed models employs metrics such as RMSE, MAE, R², and SMAPE [9]. Results reveal that ensemble models outperform other approaches, attaining the highest accuracy in predicting target variables.

By incorporating these predictors and utilizing ensemble models, the study significantly improves the accuracy of predicting session duration and energy consumption during EV charging. This advancement bears substantial implications for optimizing charging networks and effectively managing EV charging demands, fostering the seamless integration of EVs into power grid infrastructure.

Conclusion

In essence, AI is revolutionizing the automotive industry by optimizing manufacturing, driving, and maintenance. From efficient production and safer autonomous vehicles to predictive maintenance, the potential is vast. Addressing safety, ethics, and regulations is key, but the automotive landscape is undeniably on the cusp of an AI-driven transformation.

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