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Intelligent Fast Charging with Predictive Charging Profiles

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Executive Summary

Electric vehicle adoption is on the rise globally and one of the problems perceived by customers in charging is range anxiety. DC fast charging is the solution and when temperature rises above thresholds, derating algorithms are implemented by controllers, and this will impact the efficiency. This study aims at creating predefined charging profiles for efficient and user-friendly charging from past charging data. The inputs used are state of charge (SoC), departure time and temperature limits. The charge profiles avoid intermittent derating and reduced efficiency. The machine algorithms like k-nearest neighbor, lasso regression and random forest regression are used for predicting the charge profiles. The model evolution happens with incremental complexity with different input and output combinations. The AI/ML models are used for every subsequent stage of algorithm development to accommodate linear and nonlinear dependencies.

Keywords: Electric Vehicles, Hybrid Electric Vehicles, AC&DC Charging Technology, Smart Charging, Energy Management

1 Introduction

The increased green mobility adoption will accelerate electric vehicle use by 2050 and the need for efficient charging is indispensable to encourage sustainable EV use. In paper [1], they propose a novel approach in EV charging behaviour prediction that utilizes weather, traffic, and local events data along with historical charging records and focus on energy consumption predictions. In [2], the research investigates electric vehicle (EV) charging behaviour and aims to find the best method for its prediction to optimize the EV charging schedule. The paper [3] proposes a stochastic model to aid BEV drivers in making decisions about when to charge their vehicles, but charge profile prediction is not covered in the study. The study [4] aims at different time series methods to forecast EV charging load demand using historical real-world EV charging records of 25 public charging stations. In [5], EV energy consumption and session duration are predicted with minimum error. The paper [6] elaborates that individual prediction performance is essential for understanding and increasing acceptance by drivers and thus to leverage the full load shifting potential of smart charging. The survey shows that ML algorithms are widely used in charging profile and behaviour predictions. An optimal charge profile is derived without manual intervention when controller is tuned with past data.

2 Machine Learning Implementation for Charge Current Prediction

2.1 Charging Profile Prediction Method

The proposed system utilizes a machine learning algorithm to optimize charging parameters based on user selected criteria, which focuses on charging efficiency/departure time/drive range and the algorithm calculates charging time, profile, and maximum temperature as functions of the initial state of charge (SoC), initial temperature, and charging efficiency.

$$\text{Charging Profile=Optimized f}(SoC_{init}, Temp_{init})$$
$$Boundary\ conditions/Constraints = \text{Charging Efficiency, Drive Range, Departure time}$$

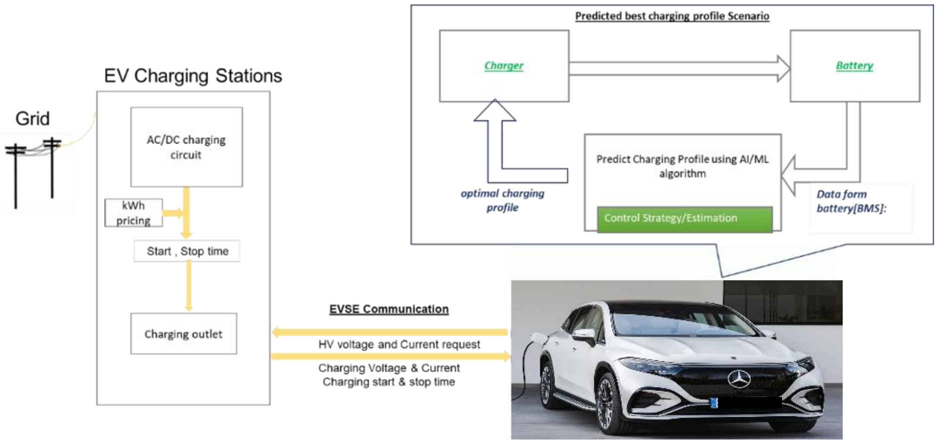

Figure 1: Charging profile prediction inside the vehicle

2.2 Implementation

The implementation of the charge profile prediction is with departure time as the major input. The environmental inputs like battery state of charge (SoC), state of health (SoH) and ambient temperature are also used for the training of the model. The outcomes expected are power/current w.r.t efficiency, time, temperature, and SoC. Identified SoC range, power, temperature for 605 cases were used to develop the model at the first stage. Power (50A:50A:500A) →11 profiles; Temperature (-25 deg C to 50 deg C) → 11 temperature; SoC range (0 to 80%, 10 to 80%, 20 to 80%, 30 to 80% and 40 to 80%) → 5 SoC ranges. The ML algorithms with multiple techniques are developed for the above cases.

2.3 K Nearest Neighbor Implementation

The k-nearest neighbors (KNN) algorithm is a non-parametric, supervised learning classifier, which uses proximity to make classifications or predictions about the grouping of an individual data point. K-fold cross-validation with a train split of 5 completed with 88% accuracy. In further implementation with more data sets, the accuracy is expected to improve. KNN also has the advantage of not requiring a separate training phase and it is easier to adapt to new data points.
Figure 2 shows the training and testing plots for charging current w.r.t time. Here, as expected in a regular charging profile, fast charging is started with high current and with the increase in SoC, current is reduced. The predicted charging profile almost matches with the trained data.

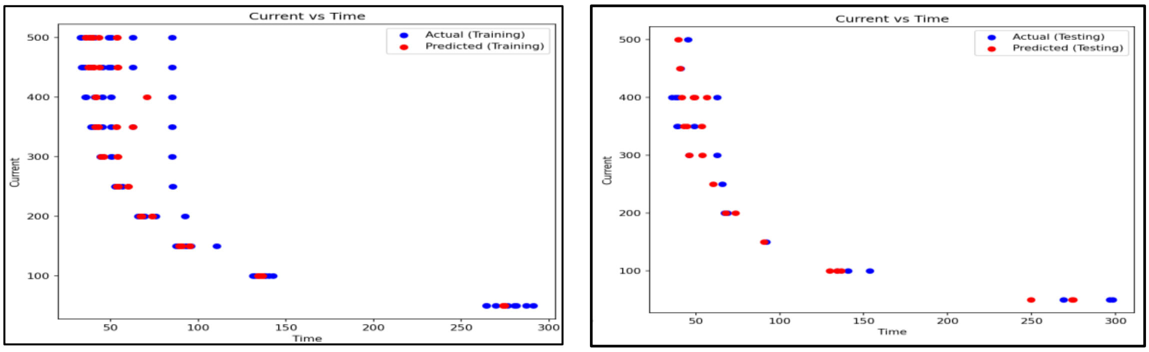

Figure 2: Training and testing plot of current vs temperature

2.4 **Lasso Regression Method**

Lasso regression automatically selects variables by setting some coefficients to zero. This is useful for feature selection because it encourages sparsity. To interpolate and extrapolate the simulation data and predict any charging current depending on the Inputs (departure time, efficiency), lasso algorithm is a best fit. The first step is to train the model with lasso regression method and test the data for model. The intermediate test scenarios were used to generate the model. The data curves are shown in Figure 3 and 4. The regression coefficient value is obtained as 0.77 (by splitting data as 80% training and 20% test data).

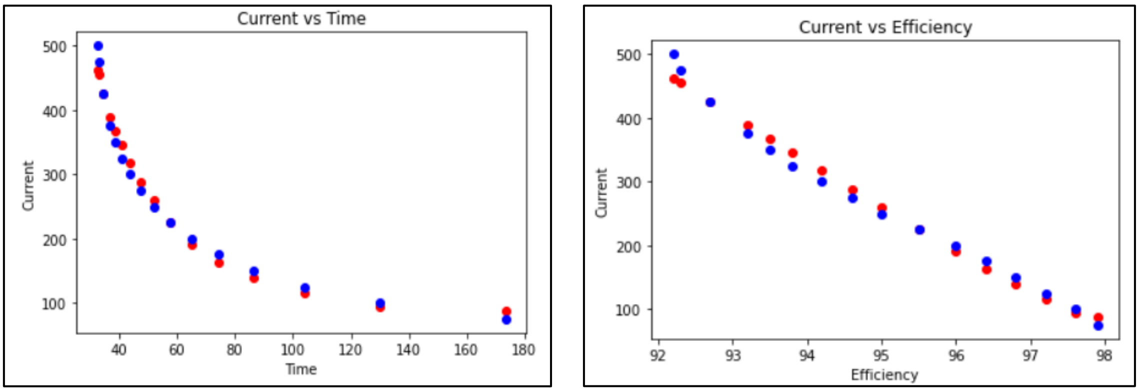

Figure 3: Training plots of current vs time & current vs efficiency profiles

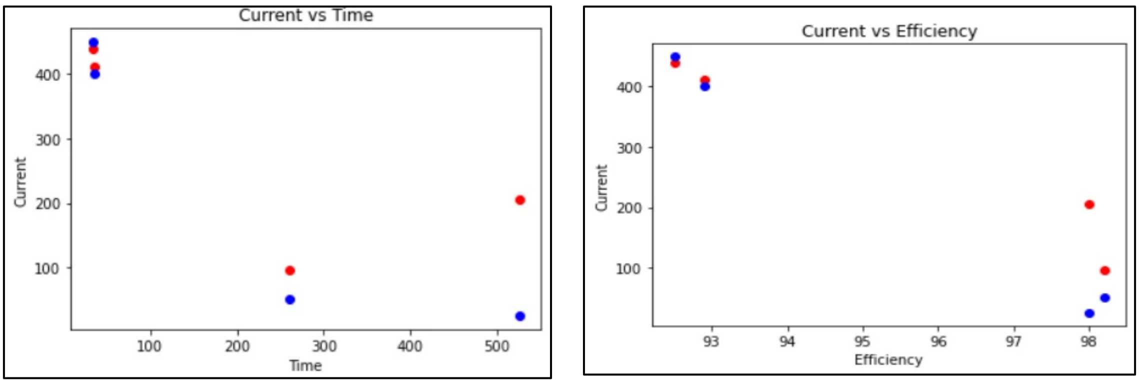

Figure 4: Testing plots of current vs time & current vs efficiency profiles

2.5 **Random Forest Regression Implementation**

Random forest algorithm combines multiple decision trees and gives continuous output. Here the final prediction is the average of all decision trees. The charging current with 50A intervals is used in training the data. The results are obtained with 94% accuracy. The training and testing plots for current w.r.t temperature and SoC are shown below.

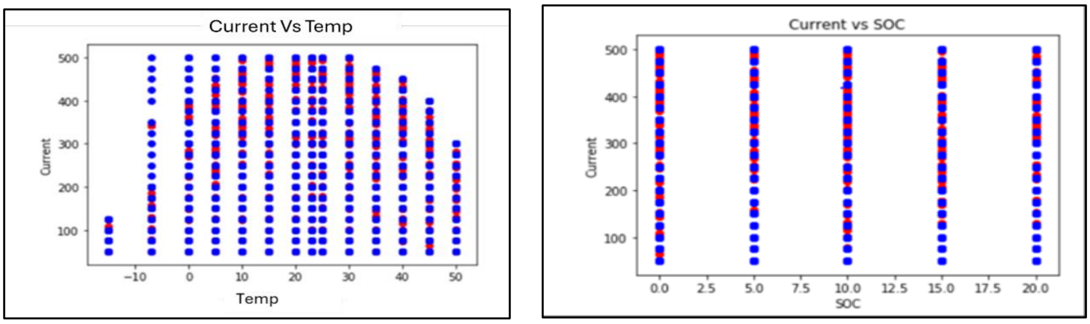

Figure 5: Training plots of current vs temperature, current vs SoC profiles

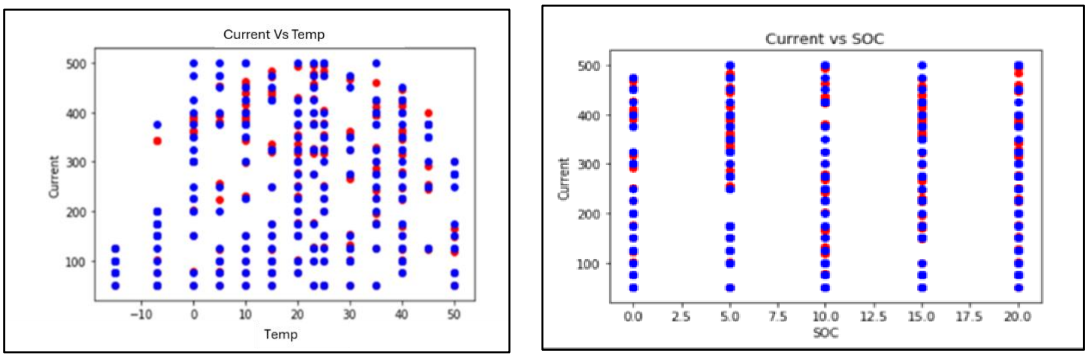

Figure 6: Testing plots of current vs temperature, current vs SoC profiles

2.6 **Results**

Figure 7, 8, and 9 shows the correlation between charging efficiency, charging time, and temperature rise with respect to the optimized charging profile at various starting temperatures. On the y-axis, the figures show the optimized charging profile, while x-axis depicts the initial temperature. i.e, Figure 7 displays charging efficiency, Figure 8 shows charging time, and Figure 9 depicts temperature rise. These results collectively highlight how the optimized charging profile varies with starting temperature, providing valuable insights, into the efficiency and thermal performance of the charging process.

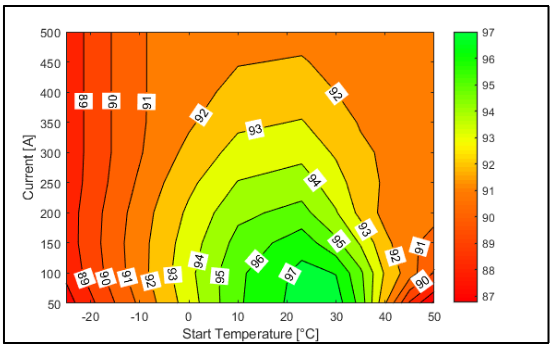

Figure 7: Charging Efficiency

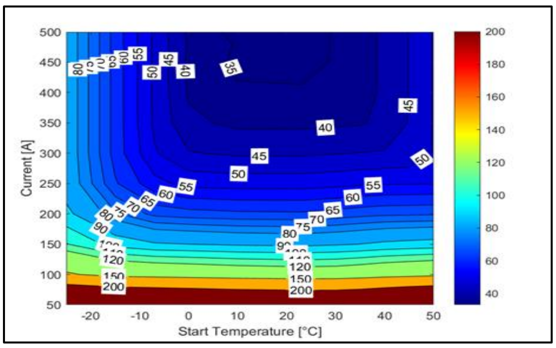

Figure 8: Charging Time

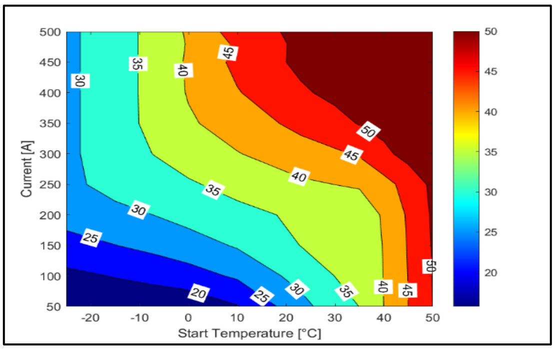

Figure 9: Battery Temperature Rise

3 Conclusion

In this study, the tuning of the ML model was carried out in different stages. The first stage involved using departure time as the input and output as charged current which is a single input single output model. In the second stage, departure time and efficiency were the input and charging current was the output. The most efficient model was derived at stage three with state of charge (SoC), battery temperature and departure time were provided as the input and the output as charging current keeping boundaries of efficiency and maximum temperature. The parameter tuning is observed to be improved with each stage. The future scope is to use advanced ML algorithms, tuned with real time data for implementation in the charge controller with a complete charge profile. This will enhance the charging efficiency, avoid charge interruptions and derating and excessive battery temperature, considering customer inputs also into account.

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Presenter Biography

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