

Prediction of Electric Vehicle Charge Profile using Battery Digital Twin

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Abstract—The transition towards vehicle electrification presents various challenges due to uncertainties in charging behavior and battery aging. This study proposes a method to generate an accurate charge profile with a battery Digital Twin (DT). The method is adaptive, has fast prediction and has low training cost. It is intended towards improving the charge scheduling for fleet operators by providing predictions on grid load and charging time. The method was tested with data from a real case study where, for a charging session, it showed an error of less than 2% for charge time and an improvement of 7% over a standard charge profile.

Index Terms—Battery Digital Twin, Charge profile generation, Charge time prediction, Battery aging

I. INTRODUCTION

Greenhouse Gas Emission (GGE) are known to cause a significant negative impact on the environment and are one of the major contributors to climate change [1] due to the prevalent usage of Internal Combustion Engine (ICE) in most modern vehicles [2]. In recent years, Battery Electric Vehicle (BEV) have been identified as a potential mitigation technology for this problem, as they have lower well-to-wheel GGE emissions than ICEs [3]. However, the complete adoption of BEVs still faces several challenges due to uncertainties in modeling charging behavior and battery aging. These challenges are particularly relevant in commercial applications, such as delivery companies and bus operators, which require large fleets of BEVs which could benefit from optimal scheduling for cost reduction.

A positive step towards achieving operational optimality for a fleet of BEV is to improve charge scheduling algorithms. Designing charging strategies has been previously studied in literature such as [4]–[6]. These strategies take into consideration grid constrain, charger constrain and battery degradation. However, they don't include the non-linear charging characteristics of a battery. These strategies could benefit from accurate prediction of charge profiles.

Several works analyze the non-linear behavior of a battery with charge profile prediction and charge time estimation. [7] develops a model-based approach to estimate the charge time. [8] on the other hand develops a regression based relation between State-of-Charge (SoC) increase and charge time. While both methods have requirements for less training data, these do not take into account the impact of temperature and battery aging.

[9] gives a method to estimate remaining charge time and generate the charge profile using a Neural Network model. [9] takes into account historical charging accuracy and compares it to real-time charging accuracy to improve its predictions. However, the method lacks recency bias and does not take into account battery aging. The method also doesn't generate a charging profile before the charging begins which would be useful for scheduling the charging of a fleet in advance. It also requires a large amount of data for the training of the models.

In this work, an adaptive DT is developed which is capable of generating a charging profile for a given charging condition. The method shows the following novelties:

- A self-calibrating DT that can capture the impact of battery aging and other changes to the system
- A fast prediction method for generating charge profile
- A methodology for low training cost and low training data requirement

The rest of the paper is divided as follows: Section II discusses the architecture of a DT and how it is applied to the battery charging use case. Section III describes the charge profile prediction algorithm. Section IV gives the implementation for a case study as well as the simulation results. The paper closes with conclusions in Section V.

II. DIGITAL TWIN FRAMEWORK

Fig. 1 shows the four types of virtual models that can be designed based on their interactions with a physical system:

- Digital Model: No interaction between system and model
- Digital Generator: Physical system follows the model
- Digital Shadow: Model follows physical system
- Digital Twin: Bi-directional exchange of data between physical and virtual system

Due to the bi-directional interaction, a DT can ensure a good state of synchronization between the virtual model and physical system, while also guaranteeing high accuracy, real-time performance, and scalability of the prediction algorithms. Further, it can be used for process optimization, observation, prediction and maintenance. For a DT of a battery in an Electric Vehicle (EV), the DT uses sensor data to calibrate itself while the Battery Management System (BMS) receives feedback to adjust its operation and control.

Fig. 2 shows the architecture of a DT for the prediction of charging profile for a fleet of BEVs (trucks). The physical

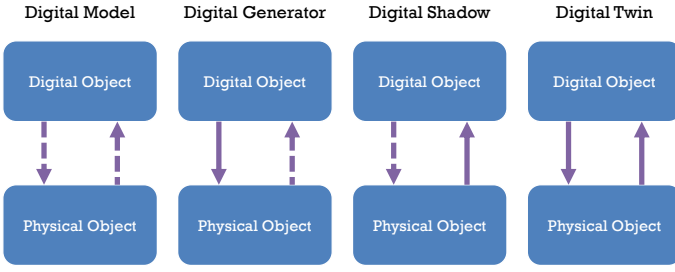


Fig. 1. Types of virtual models.

object consists of a fleet operator and a fleet of individual trucks. The objective of the fleet operator is to schedule the charging of the individual trucks which requires accurate prediction of charging time and the max load on the grid [4], [5]. These can be calculated if the charging profile (charge power vs charge time) for an individual truck is known.

The plant is the virtual model of the system within the DT and consists of Parameters and States. Parameters are the properties of a plant that change slowly while states change rapidly. For the current parameter set, the plant can generate a charging profile for a given charging condition requested by the fleet operator. This is an example of the rapid change in the state (charge profile) of the plant.

A change in parameters for the system occurs due to a change in configuration, aging, or other mechanical, electrical, or thermal effects. These are updated based on the actual charging profile from a charging session. The parameter estimation sub-module within the DT compares the actual and predicted charging profiles and updates the parameter set to minimize the error. The parameter update is done periodically to continuously adapt the DT with the most recent configuration.

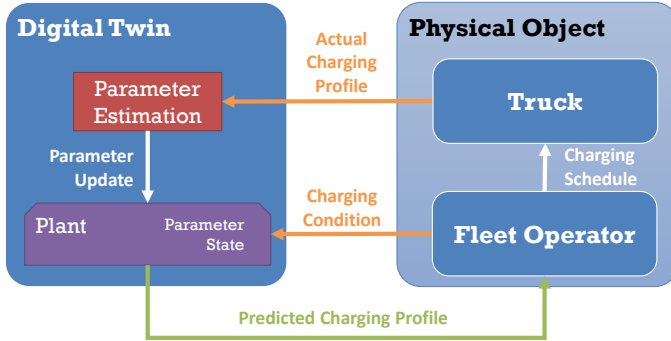


Fig. 2. Architecture of a generic DT.

III. CHARGE PROFILE PREDICTION

The objective of a charge profile prediction algorithm is to accurately predict the electrical power during a charging session based on conditions such as energy requirements, ambient temperatures, etc. This can be used to accurately compute the charging time and optimize the charging schedule for a fleet of EVs.

Fig. 3 shows a power profile during a charging session. It has three distinct segments shown as:

- (a) Ramp
- (b) Constant
- (c) Decay

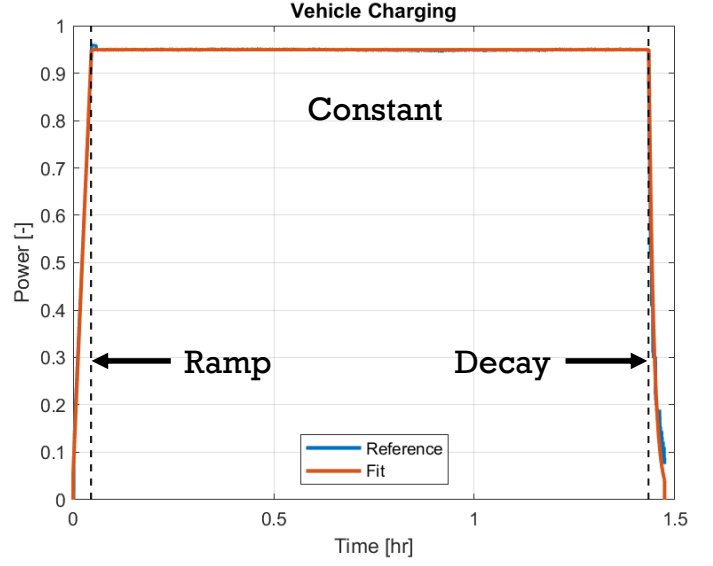


Fig. 3. Segmentation of battery charging power.

Each section can be modeled as a simplified equation such that the overall quality of the charging profile can be captured. The constant segment is defined as

$$P = P_c \quad (1)$$

where P is the output power and P_c is the charging power in the constant section. To completely model this segment the duration of this segment is also needed. This is defined as t_c . The ramp is modeled as a linear equation as

$$P = m_c \cdot t + P_s \quad (2)$$

where P_s is the charging power at the beginning of charging, t is time and m_c is the slope of charge power during ramp. The decay is modeled as an exponential equation as

$$P = P_c \cdot e^{b_c \cdot t} \quad (3)$$

where b_c is the exponential co-efficient during decay. Additionally, it is seen that there is a drop-off towards the end of the charging session before the charge power reaches 0 kW. This charging power at the end of charging is denoted by P_e . Hence, the parameter P_c , P_s , P_e , m_c , b_c and t_c are sufficient to construct the complete charging profile and determine the duration of the charging session as shown in Fig. 3.

The shape of these segments are related to battery chemistry and charger control protocol and would change with a different combination. In this work, the charging process includes a Constant Power (CP) phase where the battery voltage rises to

a cut-off point, followed by a Constant Voltage (CV) phase where the voltage is maintained until the current drops to near-zero. These phases are captured by Constant and Decay segments with the shapes representing CP and CV respectively.

A. Plant Model

The plant model should be able to compute the charge profile parameter for a given start SoC ($\underline{z}$), end SoC ($\bar{z}$), reference power request (P_r) and ambient temperature (T_a). A function is defined as an n dimensional Lookup Table (LuT) as

$$\tilde{y} = l_y^n(\tilde{u}, \tilde{U}_u, \tilde{Y}_y) \quad (4)$$

which gives the normalized output $\tilde{y}$ for a normalized input $\tilde{u}$. Additionally, $\tilde{U}_u$ is the gridded input to the LuT and $\tilde{Y}_y$ is the gridded output. Here, y denotes the variable for which the output is calculated such as P_c , P_s , P_e , etc., and u denotes the input variables such as $\bar{z}$, P_r , T_a etc.

The inputs and outputs are normalized such that they vary between 0 and 1. This is done to enforce boundedness on the data and avoid interpolation errors due to relative scaling. A variable x can be normalized from its minimum ($\underline{x}$) and maximum ($\bar{x}$) value as $\tilde{x} = (x - \underline{x})/(\bar{x} - \underline{x})$.

The start and end SoCs are already bounded between 0 and 1. Hence, they are not required to be normalized further. The reference power request varies between 0 and the maximum power limit for the charger. The ambient temperature is assumed to have minimum and maximum values of -20°C and 60°C which can be normalized using those values.

Similarly, on the output side, P_c , P_s and P_e can be normalized as P_r . However, it is seen that m_c and b_c are not bounded and can vary between 0 and $-\infty$. These variables can be normalized using $\tilde{x} = x/(x + \hat{x})$ where $\hat{x}$ is the expected value of x . For m_c and b_c the expected values are taken as 0.1 and 0.01 respectively.

Similarly, t_c is difficult to normalize as it is neither sufficiently bounded nor has a clearly defined expected value. Hence, instead of using a LuT, it is computed by an alternate method using the energy throughput (E_{th}) of the battery during the charging process. t_c is calculated such that the energy throughput of the reference and fitted charging curve are equal. E_{th} can be calculated using LuT and normalized with limits of 0 and the maximum battery capacity.

Hence, (4) is defined as a 4-D LuT function ($n = 4$) with $y \in \{P_c, P_s, P_e, m_c, b_c, E_{th}\}$ and $u \in \{\bar{z}, \underline{z}, P_r, T_a\}$.

B. Prediction

The input to the plant are: $\bar{z}$, $\underline{z}$, P_r and T_a . The output is the expected charge profile. The charge profile is a function of the output variables: P_c , P_s , P_e , m_c , b_c and t_c . The Algorithm 1 can be used to predict the charge profile.

C. Parameter Update

The parameters of the DT are the gridded output matrices ($\tilde{Y}_y$) for the different LuTs. These are incrementally updated every time the battery is charged. In this way, the cost of

Algorithm 1 Charge profile prediction algorithm.

Require: $\underline{z}$, $\bar{z}$, P_r , T_a

- 1: Normalize inputs as $\tilde{z}$, $\tilde{\bar{z}}$, $\tilde{P}_r$, $\tilde{T}_a$
- 2: Calculate $\tilde{P}_c$ using $l_{P_c}^4()$
- 3: Calculate $\tilde{E}_{th}$ using $l_{E_{th}}^4()$
- 4: Calculate $\tilde{m}_c$ using $l_{m_c}^4()$
- 5: Calculate $\tilde{b}_c$ using $l_{b_c}^4()$
- 6: Calculate $\tilde{P}_s$ using $l_{P_s}^4()$
- 7: Calculate $\tilde{P}_e$ using $l_{P_e}^4()$
- 8: Denormalize outputs as P_c , E_{th} , P_s , P_e , m_c , b_c
- 9: Calculate t_c such that the fitted energy throughput is equal to E_{th}
- 10: Generate charge profile from P_c , P_s , P_e , m_c , b_c , t_c

parameter update is low as the model isn't required to be trained for the complete history of the battery operation but only for the last step.

The gridded output matrices $\tilde{Y}_y$ for a output variable y is updated as

$$\tilde{Y}_y = \tilde{Y}_y + \Delta\tilde{y} \cdot f_y \quad (5)$$

where $\Delta\tilde{y}$ is the error between the measured and predicted values of y and f_y is the update factor. f_y is calculated as $1 - r_u^2/(r_u^2 + w_u)$ where r_u is the radial distance and w_u is the weighing factor. r_u^2 is further calculated as $\sum(\tilde{u} - \tilde{U}_u)^2$.

Fig. 4 shows the relation between r_u and f_y , where f_y is 1 at $r_u = 0$ and asymptotically goes to 0 with increase in r_u . This formulation updates $\tilde{Y}_y$ at the neighborhood of the charging condition (u) while the influence of update is smaller the further one moves from u . The strength of the update is determined by tuning w_u . Hence, a wider range of the model can be trained with less number of data.

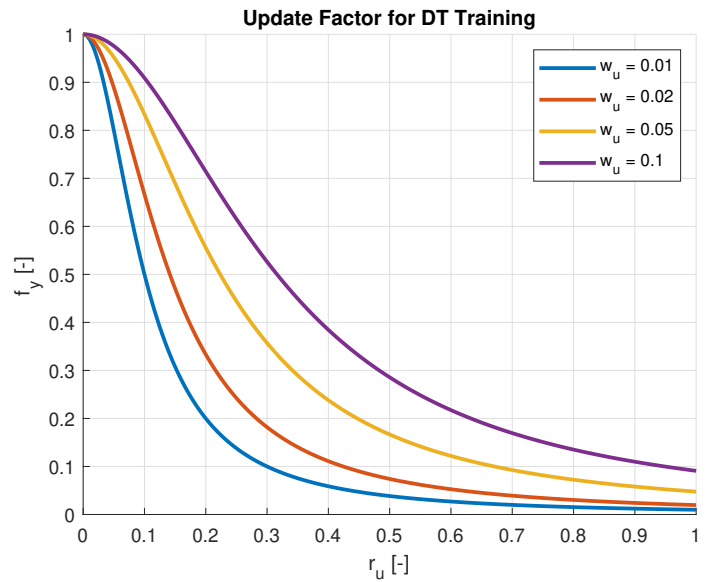


Fig. 4. Relation between radial distance r_u and update factor f_y .

The Algorithm 2 can be used to update the parameters of the charge profile generation DT.

Algorithm 2 Charge profile parameter estimation algorithm.

Require: $\bar{z}, \bar{z}, P_r, T_a, P_c, P_s, P_e, m_c, b_c$ and E_{th}

- 1: Normalize inputs as $\tilde{z}, \tilde{z}, \tilde{P}_r, \tilde{T}_a, \tilde{P}_c, \tilde{P}_s, \tilde{P}_e, \tilde{m}_c, \tilde{b}_c, \tilde{E}_{th}$
 - 2: Update Y_{P_c} using $\Delta \tilde{P}_c$
 - 3: Update $Y_{E_{th}}$ using $\Delta \tilde{E}_{th}$
 - 4: Update Y_{m_c} using $\Delta \tilde{m}_c$
 - 5: Update Y_{b_c} using $\Delta \tilde{b}_c$
 - 6: Update Y_{P_s} using $\Delta \tilde{P}_s$
 - 7: Update Y_{P_e} using $\Delta \tilde{P}_e$
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IV. RESULTS AND DISCUSSION

The method is applied to the data collected for 7 months from a medium-duty logistic truck with an LFP battery pack. Fig. 5 shows the variation of start and end SoC during this period. It is seen that the battery is always charged above 80 % (except for a data point on July 27), while the start SoC has more variation. Fig. 6 shows the variation of ambient temperature during this period between 9 °C and 27 °C. A higher variation in data is better for both training and validation as the method can be tested on differing conditions.

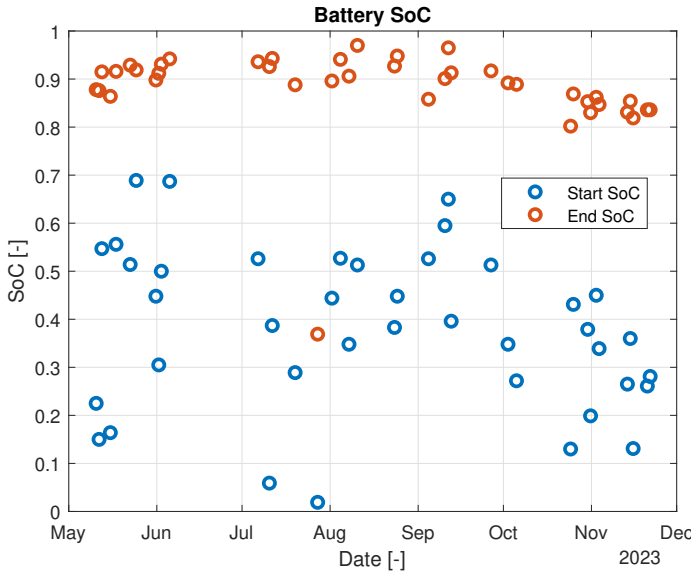


Fig. 5. Battery SoC during charging sessions.

For every charging session, the fleet operator is assumed to make a charge profile request with the corresponding charging conditions. The algorithm is used to predict the output variables and the charge time. The output variables are then compared to the actual data and the plant parameters are updated. This step is successively repeated for the entire dataset.

The objective of the charge profile prediction algorithm is to reduce the error for the charge time prediction. An additional objective is to prioritize the overestimation of charge

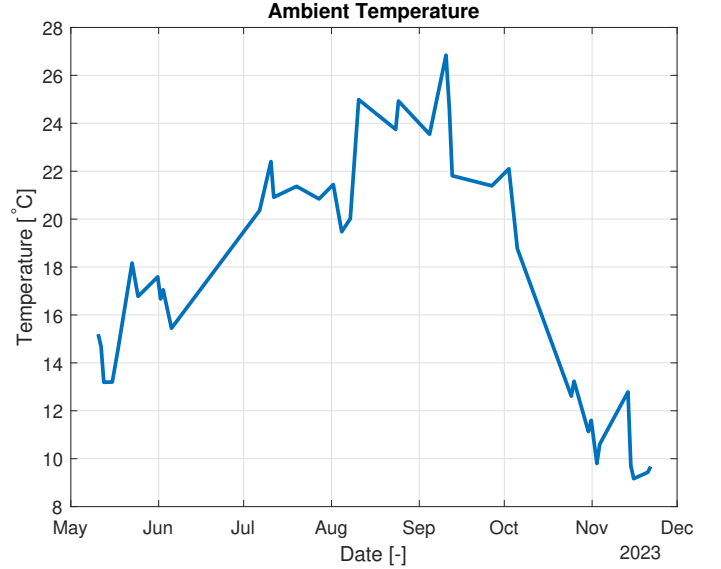


Fig. 6. Ambient temperature during charging sessions.

time as opposed to underestimation. It is easier to maintain a schedule if the charge time is overestimated as that scenario would require the vehicle to stay idle at the charging depot for an additional duration. However, if the charge time is underestimation the vehicle will certainly miss the start of its next assignment.

Fig. 7 shows the reference and predicted charging time while Fig. 8 shows the relative error for the same. It is seen that the prediction is poor at the beginning and improves with successive training. The error for the moving average is less than 2 % for the last sample. Three outliers can be seen at July 27, Sept 10 and Nov 15 which have significant deviation from the moving average line. The data on July 27 is an outlier for the SoC condition while Sept 10 and Nov 15 have the highest and lowest ambient temperatures respectively. Hence, it is seen that the algorithm is limited in predicting the charge time at the limits of input conditions.

The poor predictions for these conditions are also due to the frequency of the training data which is lower than the availability from the field. During the real-time operation of the vehicle, the DT will receive data from at least 1 charging session per day to update the plant parameters. However for the results shown in Fig. 8, only 2 charging sessions per week are available. The training for the method is less abrupt with high-frequency data as the chances of encountering a sudden jump to a new charging condition are reduced.

The method also attempts to fulfill its additional objective by tuning the plant parameters to overestimate the charge time. This is seen in Fig. 9 where the initialization and training factor is selected to make the prediction error positive for majority of cases. This objective is applied to individual charging segments for robustness. However, the current implementation can only fulfill this criterion under limited circumstances and future implementations must satisfy this condition explicitly.

Fig. 10 shows the correlation between the errors in the

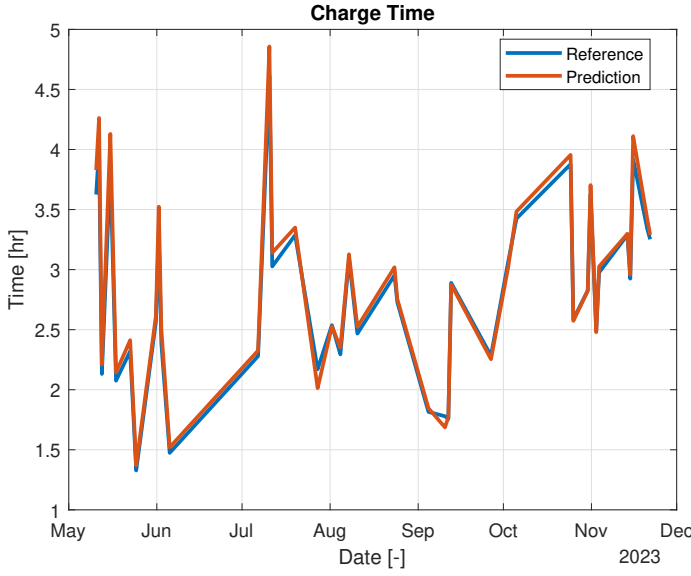


Fig. 7. Charging time during charging sessions.

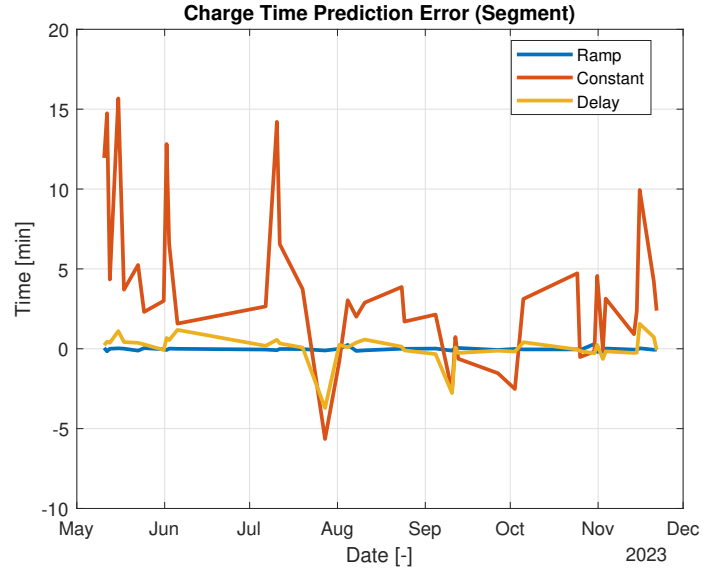


Fig. 9. Error in charging time for different segments during charging sessions.

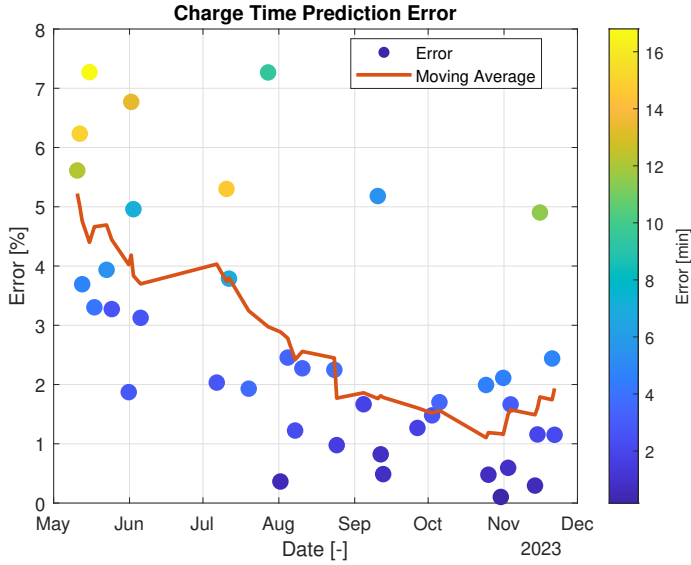


Fig. 8. Error in charging time during charging sessions.

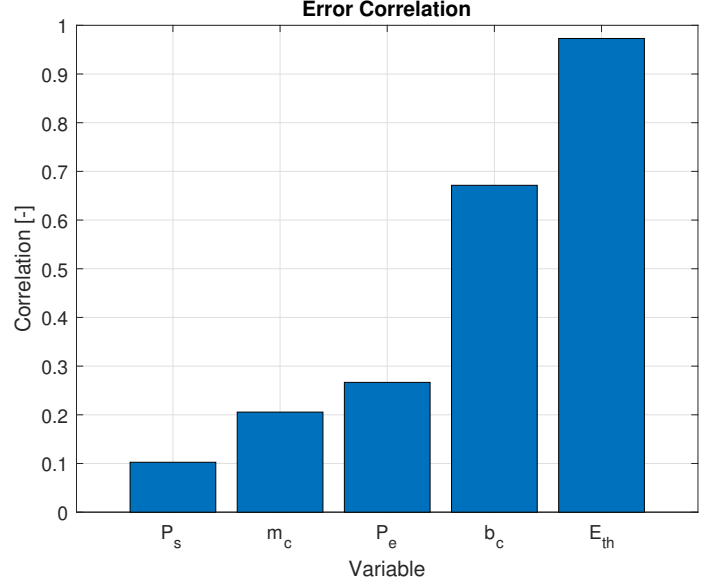


Fig. 10. Correlation between errors in predicted output variables and charge time.

predicted output variables and charge time. It is seen that the energy throughput has the highest correlation followed by the coefficient of decay. Hence, these two variables have the largest contribution to the charge time prediction error. Additionally, it can be seen from the data that the slope for the ramp segment remains constant for all data points. Hence, it has a low correlation to charge time prediction error. This is likely due to the charger control which ramps up the charge power at the same rate irrespective of the battery behaviour.

The purpose of the development of the charge profile prediction DT is to improve the charge scheduling operation for a fleet of BEVs. The goal is to enable a fleet operator to schedule the charging of individual vehicles in a fleet such that their operational deadlines are met. Commonly, a fleet

operator uses the Standard charging profile from Fig. 11 to make the schedule while the actual charge profile is closer to the Predicted.

The key challenge faced by a fleet operator while using the Standard profile is the underestimation of the charge time. To compensate for this the fleet operators keep an arbitrarily large buffer between the end of charging and the start of the next vehicle assignment. Hence, an accurate prediction of charge time helps the fleet operator reduce this overhead and plan the fleet charging more efficiently.

An improvement by the Predicted profile over the Standard profile is shown in Fig. 12. Here, we see that the charge time for the Predicted profile is similar in accuracy to the Standard

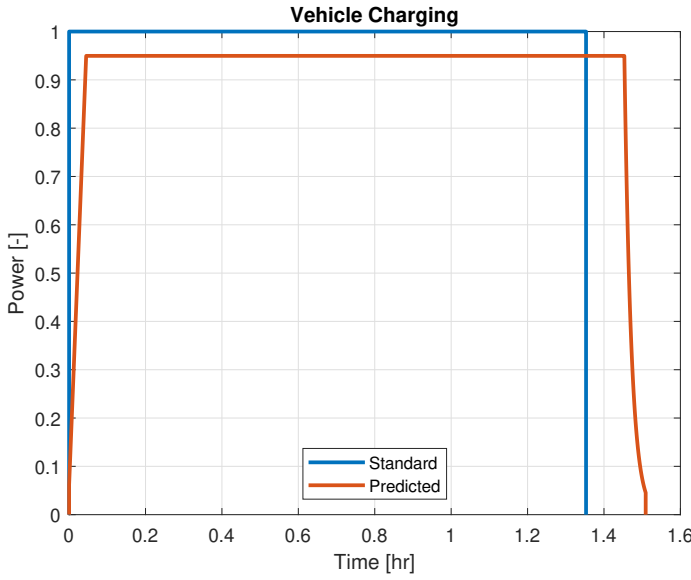


Fig. 11. Charge profile for a charging session.

profile at the beginning but continuously improves with training. The moving average converges to an improvement of 5% with the highest achieved improvement of 7%.

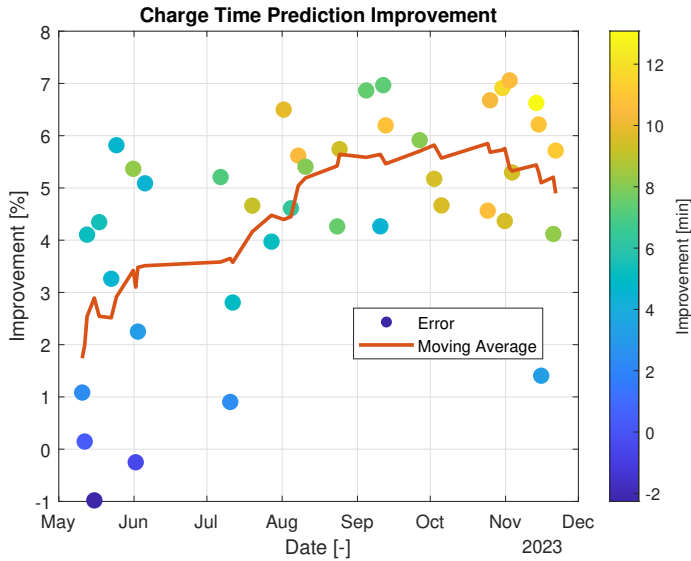


Fig. 12. Improvement in charging time over Standard charging profile.

V. CONCLUSION

In this study, a method for charge profile generation was developed for a BEV which can be implemented in a DT framework. The method is self-calibrating and takes into account the long-term changes to the behavior of the battery such as aging. It also has real-time prediction capabilities with low training costs due to an incremental update strategy. The method is aimed at improving the fleet scheduling for fleet operators.

The method is applied to a medium-duty logistic truck and the accuracy of prediction for charge time is assessed. It was found that the error has a decreasing trend with successive training. For the last sample, an error of less than 2% was found for charge time. The method also shows an improvement of up to 7% compared to a Standard profile used for charge planning by fleet operators.

Future work will extend this method to an in-field implementation with bi-directional communication with a fleet operator and a fleet of trucks. The prediction method will be improved by including additional input variables such as battery temperature and objectives such as overestimation of charge time. Additionally, advanced machining learning algorithms and AI techniques will be investigated. Lastly, other types of battery chemistry and charger combinations will be investigated to determine the adaptability of this method to different scenarios.

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