Driving Pattern Prediction for the Optimization of Wear Leveling-Aware Cell Balancing

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***Abstract*—With the rapid adoption of electric vehicles (EVs), extending battery lifespan has become increasingly important. Battery aging is accelerated by frequent charge transfers used in active cell balancing. Wear level-aware balancing reduces this impact by strategically scheduling balancing activities based on predicted driving patterns. However, this method relies on knowledge of future driving missions, which is typically unavailable. This paper presents simulation-based strategies for predicting future driving missions, including statistical methods and Long-Short Term Memory (LSTM) deep learning models. Both static and dynamic prediction approaches are developed and evaluated through simulations. Results indicate that predictive methods significantly extend battery lifespan while maintaining manageable risks associated with prediction inaccuracies. Future research directions are also discussed.**

***Index Terms*—Electric Vehicles, Active Balancing, Battery Management, Wear Leveling, Driving Prediction, Simulation, Deep Learning.**

I. Introduction

As the world begins to shift towards electric vehicles (EVs), there is great concern about the longevity of EV batteries. An EV battery pack is composed of several smaller cells connected in a grid, which means that once a single cell is damaged due to its level of charge being below 20%, the entire battery pack stops functioning. Over time, a cell's maximum charge retention capacity will decrease in a process known as battery aging. Manufacturing variabilities combined with unequal exposure to elements such as heat result in cells aging at different rates, leading to them having unalike maximum charge capacities.

Since charging stops when a single cell reaches its maximum charge capacity, the battery will become unbalanced because different cells will contain different amounts of charge. Unfortunately, this is problematic, as the cell that ages most rapidly will be the one that goes the fastest below the 20% threshold, leading to a shorter battery lifespan as charging is needed more frequently.

There are processes in place to solve this problem, most notably active balancing. Active balancing occurs when the vehicle is in an idle state, and the battery management system transfers charges between cells to bring the charge levels together. Typically, active balancing is done opportunistically, whenever there is an idle period. However, this is not ideal because the near-constant flow of charge between cells also results in increased cell aging.

A solution that improves upon active balancing to limit its effect on cell aging is wear level-aware balancing as proposed in [1]. The principle of this solution is that given the future driving mission, defined as the driving pattern for a certain period of time, balancing activities can be strategically scheduled to minimize the amount of charge transfer while maintaining the ability to complete the mission, thus minimizing cell aging.

The main caveat with wear level-aware balancing is the assumption that the future mission is available, as this data is not available in practice. The goal of this report is to develop strategies for predicting the future mission and modeling their effectiveness using a computer simulation.

First, some related work will be presented, with respect to the active balancing problem and the problem of predicting future destinations of a vehicle. Next, the setup for the static simulation and the development of the first four strategies will be explained. Then, the development of the dynamic simulation and the two strategies being used for that will be discussed. We will visualize the results and conclusions from the study and conclude with some ideas for future work.

II. Related Work

This section will explore related work on the topics of active balancing as well as driving destination prediction.

A. Active Balancing

Active balancing has been thoroughly studied. In [6], the active cell balancing process was time-optimized using a mixed integer linear programming problem to take advantage of linear nature of active balancing. Similarly, the optimization of active balancing with respect to the level of energy dissipation was obtained in [5]. Most importantly, the work in [1] sets up the optimization for the scheduling of active balancing activities given knowledge of future driving activities. This particular optimization problem lays the groundwork for the work done in this report and serves as a benchmark which can be used to judge the effectiveness of the strategies implemented in this study. Additionally, Hoekstra et al. [3] proposed a model-predictive control strategy for optimizing active cell balancing, achieving significant improvements in battery lifespan and range predictions.

B. Destination Prediction

Previous work in destination prediction often involved the usage of various machine learning and deep learning models. The use of Long-Short Term Memory (LSTM) models in destination prediction was explored in [2], using temporal and spatial data alongside further contextual data to make a destination prediction.

In [4], a Hidden Markov model was built to cluster the driver's historical trip data to make predictions.

The work done in this report differs from previous work in that the prediction being made in this report is for multiple future destinations. That is, the scope of the problem is being widened from predicting the single destination for one trip to predicting all of the destinations a driver will travel to in one day, based on simulated historical data.

This modeling will be combined with a battery simulation to create a system that is able to intelligently schedule the active balancing activities of an EV without knowledge of future driving activities to minimize the aging effects of active balancing while maintaining the ability to complete the mission.

Recent advancements in destination prediction include the usage of Bidirectional LSTM models with attention mechanisms to enhance prediction accuracy by effectively utilizing temporal and spatial data [8]. Furthermore, Tayarani and Hanif [7] employed machine learning models, specifically Bidirectional LSTMs, to accurately forecast electric vehicle destinations and charging behaviors, substantially reducing unnecessary charging events.

III. Problem Setup

Due to a lack of a driving dataset containing the appropriate features to solve this problem, the data used for this experiment was randomly generated. This generation was done using a graph in which nodes were locations and edges represented roads between locations, with each outgoing edge from a node assigned a probability that it would be traveled from the source node, a random travel duration, and a current.

Graphs were constructed by creating a connected Watts-Strogatz digraph using 12 nodes of degree 4, with random probabilities assigned to each edge. Each edge was also randomly assigned a random travel duration and current from a normal distribution. A node was randomly assigned to be a charging simulation and was assumed to represent home.

We now define the driving sequence of length n, which is an n-tuple containing the nodes $(a_1, a_2, ..., a_n)$, where a_1 is the node the driver begins their day at and a_2 is the first node they visit. To generate data, random walks of length n were computed to simulate driving sequences of length n. The driving mission, more precisely defined as a sequence of tuples containing a time and a current for a drive alternating between driving and idle states, could then easily be obtained for simulation.

IV. Methodology

This section describes the strategies developed to tackle the prediction task as well as the simulations used to test them.

A. Static Simulation

The main approach to solve the problem of unknown future data was to use a representative mission to solve the balancing problem, and simulate the effectiveness of the resulting balancing schedule on the true mission.

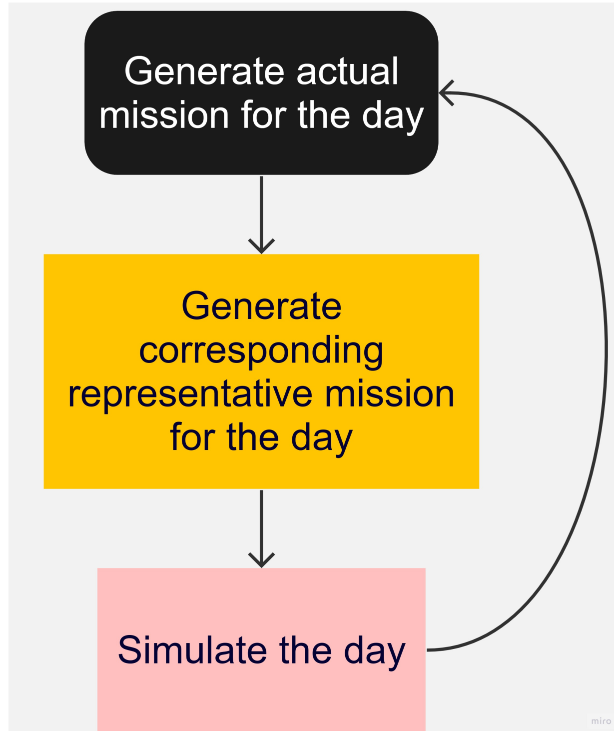

Fig. 1: Static Simulation Process

As shown in Figure 1, the static simulation process begins with the generation of the weekly mission whose data will be used in the simulation. Next, the representative mission is generated for that week, and its driving data is used to solve the balance scheduling optimization schedule. The resulting balance schedule will be used on the actual mission generated first. The process repeats for a specified time period.

Three kinds of representative missions were tested on the simulation. The average mission is created by simulating 1000 random missions from a graph and then creating a mission by averaging the times and currents for each tuple in the sequence. The most likely mission of length n involved traveling the edge of highest probability n times.

Lastly, we have the deep learning predicted mission of length n. This involved an extra assumption that we knew the first k steps of the future mission and were trying to predict the remaining $n-k$ steps. The first attempted approach to predicting multiple steps at once involved the creation of a multi-task classification model that would have $n-k$ separate output layers and a 64 Long Short-Term Memory (LSTM) node input layer. However, this approach resulted in low accuracies, likely due to underfitting.

The second approach involved training a model predicting the next visited node from k nodes and then using a shifting technique to predict multiple days into the future. Consider the sequence of visited nodes $(a_1, a_2, ..., a_n)$, where n is the mission length. We train a model to predict the next node from k previous nodes using randomly generated training data. After this, we feed it the node sequence $(a_1, a_2, ..., a_k)$ to predict the

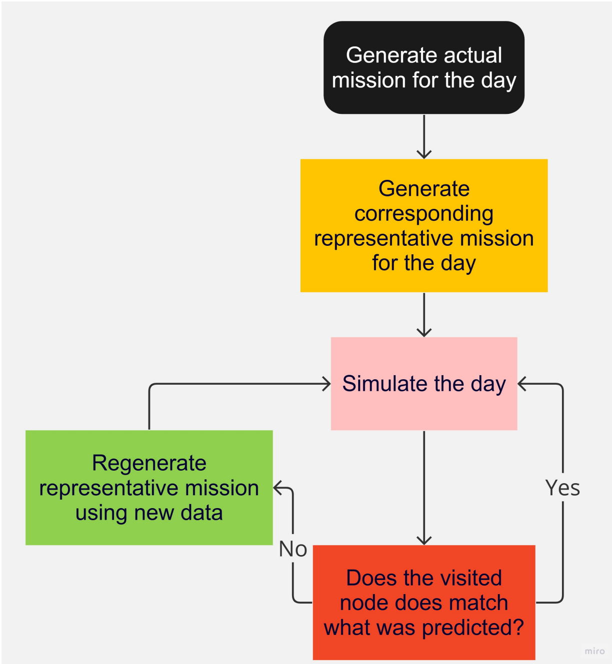

Fig. 2: Dynamic Simulation Process

node a_{k+1}. Then, we shift one node down and feed the model the sequence $(a_2, a_3, ..., a_{k+1})$ to predict a_{k+2}. We continue this process until we have successfully made predictions for all nodes from a_{k+1} to a_n. This approach was more successful, as models achieved success rates from $75\% - 95\%$ for predicting a single destination.

B. Dynamic Simulation

The work discussed up to this point involves making predictions statically, meaning that the mission for a particular day was predicted only once at the beginning of that day. This section looks to build upon that work to create a system that is dynamic and makes predictions to correct its mistakes.

This system starts by making a prediction for the mission of length n at the beginning of the day using the most likely mission strategy. It proceeds to simulate the day, with the condition that if the kth predicted node does not match the kth actual node, a new prediction will be formulated.

Two strategies were used for the re-prediction process. The first involves training a model to predict one node ahead from k nodes, and then using the shifting strategy discussed earlier to predict the nodes from the $k + 1 - n$ indices. The other option tested was to recalculate the most likely path of length $n - k$ starting from the kth node and replaced the nodes from index k in the mission with this path.

V. Results

The main results of this report were compiled by running 34 simulations in which each of the mission prediction techniques was tested on a generated scenario for a 6 month long period. From these simulations, the total predicted lifespan was extrapolated and the errors made in going below the charge threshold were recorded.

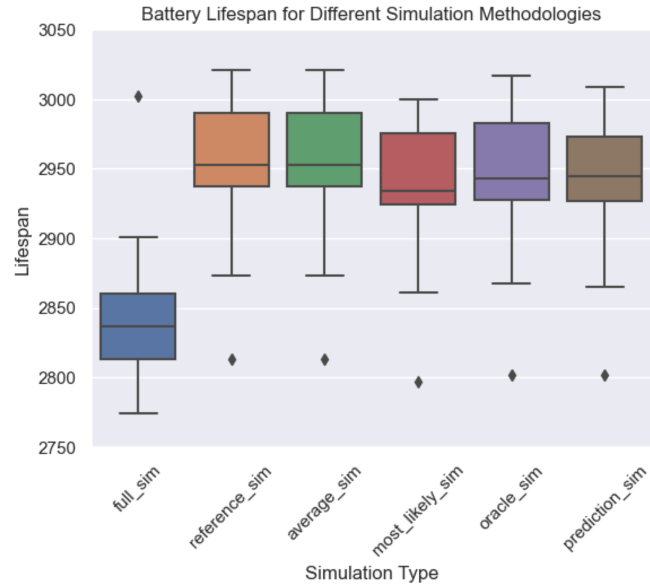

Fig. 3: Battery Lifespan in Days

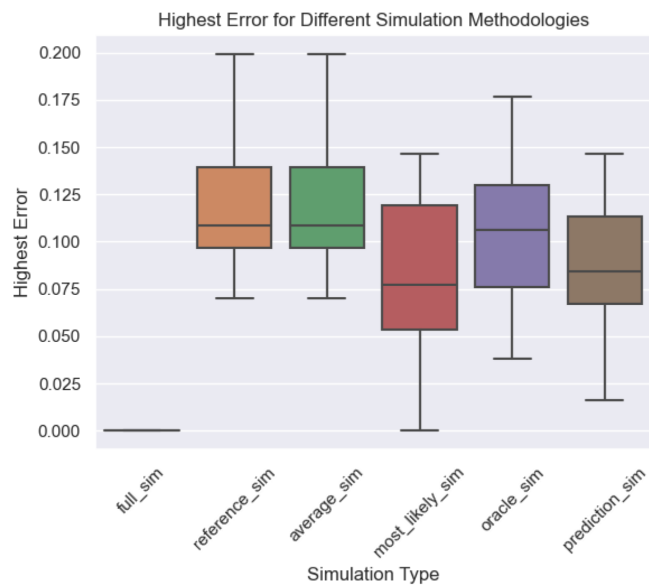

Fig. 4: Simulation Error in Charge Percentage

Figure 3 depicts the distributions of the resulting battery lifespans across the 34 simulations for each of the different simulation types. Full_sim refers to the full balancing technique, reference_sim refers to the no balancing technique, average_sim refers to the technique using the average mission, most_likely_sim refers to the technique using the most likely mission, and prediction_sim refers to the technique using the predictive LSTM model. It is clear that all of the techniques improve the battery lifespan by about 100 days after a simulation of 6 months.

Figure 4 shows the highest margin by which the battery charge dropped below the safe threshold during the simulation. In a sense, this measures the accuracy of the predictions made by the various techniques as the more accurately the calculated mission matches the actual mission, the smaller the mistakes. The full balancing simulation is perfectly accurate as it balances at every possible opportunity, bringing the chance of an error to zero. The most likely representative mission and the predictive deep learning model had the next two smallest errors. The idea here is that there is a trade-off, where we risk dipping below the safe threshold and potentially damage the battery in exchange for a longer overall lifespan. However, the risk taken when employing these techniques can be mitigated by artificially increasing the programmed threshold to a point where even the largest dips do not cross the actual threshold and damage the battery.

VI. Future Work

There are many extensions of this project that can be completed to enhance it in the future. The strategies implemented in this paper assume that we know the length of the driving mission, so a key improvement would be to rework the simulation to remove that assumption.

The deep learning models used in this report were basic, and it may be worthwhile to run the simulation using more powerful models with deeper architectures that have been optimized using hyperparameter tuning.

Lastly, the most important thing that can be improved is the data generation process. Without a real dataset, it is hard to know whether the data and graph used represents a realistic scenario. An idea to tackle this problem would be to collect destination data from an EV user and construct an appropriate graph from this data. An algorithm could also be developed to alter this graph to create several realistic scenarios that can be used to further test the methods described in this report.

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