Sensor based Battery Life Prediction in Electric Mobility using Multimodal Neural Network

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ABSTRACT

Lithium Batteries are the powerhouses of modern electric vehicles (EVs). The measurement of the battery's state of charge (SOC) data is crucial to planning for long-distance travel and the breaks required to charge in between. In real life, the sensor data can be prone to external noise and thus the correct SOC may not be displayed accurately. To avoid this, the current manuscript proposes a multimodal neural network and sensor-based SOC prediction for long-distance EV travel plans. The proposed model is trained from real-world battery behavior on parameters such as charging/discharging trends, distance covered and environmental factors that affect the battery SOC. The proposed model learns battery discharge patterns affected by various load scenarios, making the system robust. Furthermore, this can be used for prediction based on the sensor, environmental and load conditions. The proposed technology can be extended to other applications such as drones, delivery robots, and e-bikes for optimizing efficiency, safety and route optimization.

Keywords: Battery life prediction, multimodal neural network, sensor based battery life, baseline neural network and Adaptive neural network.

I. INTRODUCTION

In today's automotive industry, there is a heavy paradigm shift over the last decade, moving from the internal combustion engine vehicle to electric vehicles (EV) [1]. EVs are a bigger boon in sustainable transportation as there is no emission, which helps in a green environment [1]. This shift also helps in handling the fading away reserves of fossil fuels and supporting climate goals [2-4]. The core of this shift lies with the battery used, which is Lithium-ion battery, a sophisticated electrochemical energy storage system that helps in the safety, economic viability and performance of the vehicle [2, 3]. The EVs not only penetrate the consumer car market but also the electric delivery vans, trucks, drones to cover the logistic sector, and public transport like bus, auto have higher reliability factor in today's era [4]. But unlike the fuel tank which is ideal cases today to combustion vehicles the provide a simple reading of the remaining quantity of the fuel in the vehicle which users are used to consume that to refill the fuel, but the battery reading is a non-linear, time-variant system which cannot to measured using a direct method [5, 6]. This complexity builds up a complex battery management system (BMS) which is considered the core part of the battery pack[6, 7]. The major work of a battery management system is to predict the state of charge (SoC) and remaining useful life (RUL) [8, 9]. The unreliable prediction from the system is not safe for the EV driver which leads to the range anxiety known as the fear of stranding due to a 0% battery [9]. An unreliable system like predicting the wrong values can lead to unexpected shutdowns, faster battery degradation and inefficient route/travel planning in modern electric mobility. For this reason the industry is moving away from the basic estimation methods, such as Ampere-hour counting, and moving towards complex model-based model-based approaches like Kalman Filters and, more recently, data-driven machine learning techniques [10-12].

Even with these improvements, a major issue is present in the architecture of the current BMS is the dependency on a single sensor output data [13]. Most of the contemporary predictive models depend on the sensor readings of voltage, Current and Temperature to predict the battery SOC and RUL [14]. This kind of unimodal dependency is not suitable in the real-world situations even though this works effectively in a well-controlled lab environment [12-14]. This won't be suitable in real-world operations because the sensors used are put through a rough vibrations electromagnetic interference (EMI), and thermal drift, this can lead to a nose injection or a data loss [14]. If the single sensor fails or is subjected to noise the basic battery SOC and RUL also fail as it depends completely on the failed sensor reading to perform the range predictions and put the user safety to risk [15].

To be exact the existing architecture of the BMS is not aware of the main context behind. The current architecture treats the battery as a separate component by neglecting the major impact of the external operational variables [15-17]. Let's take an EV robot used for delivery carrying a payload uphill in a scorching temperature will discharge the battery faster than the delivery robot travels in a flat road with the same readings initially [16, 17]. So the existing model doesn't have the input variables like the payload, topography, the outside temperature and weather, which in turn make the

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model struggle to adapt to the changes in load weight and other environmental conditions changes.

To address these limitations, this paper proposes a novel multimodal architecture designed for robust, sensor-independent battery life prediction. This system does not only depend on electrical measurements (voltage, current) but also on the external data (Payload, Terrain, Environmental factors). A multimodal system using neural networks and sensor data is proposed in this system which learns to weigh input sources dynamically. This makes the model work with high prediction accuracy even if we receive noisy data from the primary measuring sensors. This research aims to bridge the gap between idealized lab-based algorithms and the messy, unpredictable reality of electric mobility, offering a path toward smarter, fault-tolerant Battery Management Systems.

II. LITERATURE SURVEY

The global transformation towards sustainable mobility has triggered the faster adoption of EVs [1, 2]. This made the Lithium-ion battery as the major component in the modern green mobility ecosystem [3]. Since this is the case the battery pack becomes the primary energy storage system so the battery's performance immediately affects the safety, operational efficiency and range of the Evs [1-5]. Therefore the brain of this unit the BMS has also improved from a basic monitoring system into a sophisticated control unit that accounts for the SOC estimation, state-of-health (SOH) prediction, and thermal regulation [4-7]. However, the legacy estimation techniques like the Ampere-hour counting and open circuit voltage (OCV) measurement has been the base methods, these are widely recognized as insufficient for the emerging applications [4-6]. The Ampere-hour counting method leads to error calculations over time due to the sensor drift, and the OCV method requires the battery to be in the rest position, so using this in running vehicles is not a viable option [8]. Latest literature indicates a significant shift towards data-driven methods, using Artificial Intelligence and integrating the internet of things (IoT) to handle the non-linear future complicated behavior of the battery [7-13].

An essential part of the current research focuses on improving the SOC and SOH estimation accuracy by use of the machine learning algorithms. Recurrent Neural Networks (RNNs), specifically Long Short-Term Memory (LSTM) networks have developed into superior methodology among the multiple machine learning architectures [17-21]. Specifically for the BMS application the LSTM are the best suited because of their ability to retain the long-term dependencies in time series data as per the literature [21]. LSTM has the ability to learn the past historical trends of the current and voltage values which in turn allows them to model detailed dynamics of the charging and discharging behavior even if the SOC values are imperfect initially [22]. This is not possible with the feed forward network on machine learning [22]. Latest studies tell us that the stacked LSTM configurations can reduce the errors in estimation and this can be achieved by reading hysteresis effects inherent in Lithium-ion chemistries [23, 24]. With these challenges in EV charging, a robust alternative to model-based Kalman Filters is required which in turn involves complex matrix operations and precise electrochemical modeling [25-27].

Researchers have been doing further investigation on the hybrid deep learning architectures to further enhance predication capabilities [28]. Fusing convolutional neural networks (CNN) with LSTM models has been the current trend in the research world. In this architecture, the LSTM layer processes the temporal sequences while the CNN layers help in extracting the spatial features from multi-dimensional inputs such voltage, current and temperature [29-31]. This Integrated approach has helped in improved performance in the context of convergence speed and stability [29]. From multiple experimental results the CNN-LSTM hybrid models can maintain mean absolute errors (MAE) below 1.5% even on unfavorable conditions like changing ambient temperatures, varying impedance in cold-weather operations [28]. Extreme learning machines (ELM) have attained attention for applications requiring lower computational latency [29]. ELM models, when optimized with meta-heuristic techniques like gravitational search algorithms (GSA) have given a tremendous train efficiency across driving cycles such as the federal urban driving schedule (FUDS). This offers an effective solution for embedded BMS where processing power is limited [31].

Along with the development in the section of algorithmic estimations, there are heavy advancements happening in the architecture of the BMS itself by adding the IoT [17-21]. The literature explains the transformation of an isolated, on-board processing system toward a cloud-connected ecosystem. Today microcontrollers like NodeMCU, Raspberry Pi are used to receive the high-frequency sensor data and send it to the cloud platforms and this is how modern IoT-enabled BMS are built. By this we are unlocking the potential for "Digital Twins" and remote predictive analytics. [32] All the heavy computational tasks are performed in the cloud so these systems can incorporate the complex deep learning models, these heavy computations cannot be run in the local microcontrollers. In this further, we bring in facilities like predictive maintenance and automatic servicing. Research tells that on analyzing the aggregated fleet data, cloud-based BMS algorithms can identify subtle anomalies like early-stage cell imbalances or abnormal thermal spikes before they lead to a critical failure. This kind of approach can help in reducing the downtime of the vehicle by 30-50%, which lowers the total cost of ownership for fleet operators [32-34].

Physical charging infrastructure and cell balancing protocols are the major branches of energy management [35]. Cell consistency is important because inefficiencies in these can cause a weak link problem, which can cause issues with the capacity of the entire pack due to a single degraded cell [36]. Also, the modern academic works have explored AI-driven passive and active balancing strategies. Reinforcement Learning (RL) agents, for instance, are being trained to optimize the switching sequences of balancing circuits. These agents are more effective than fixed-threshold logic in minimizing the energy dissipation through heat and ensure uniform charge distribution after learning the optimal discharge paths. In addition to this an algorithm called intelligent charge scheduling is being used to associate with smart grids that helps the vehicle charging prioritization based on the battery health status and vehicle's urgency, this also mitigates the peak hours grid stress [37].

Even though there are multiple technological improvements, the literature reveals major gaps that are not being addressed, particularly concerning data fidelity and robustness [37]. Largely, most of the data-driven models heavily depend on the input data being pure and noise-free. In laboratory settings, high-precision sensors provide accurate readings of voltage, current, and temperature. However, in the real-world scenario the electric mobility sensors are gone through heavy physical vibrations, subjected to electromagnetic interference (EMI) and thermal drift, which leads to a potential data loss and heavy signal noise. Present deep learning models will learn the noisy data instead of filtering it, which leads to wrong predictions when sensor fidelity deteriorates [38].

In existing research, it is mostly a single model that focuses on the electrical parameters (voltage and current) and thermal parameters (temperature) [39-41]. In this type of system, either the model is completely unaware of the contextual data or the multimodal frameworks that incorporate auxiliary data (like payload weight, topographical data, and route information) goes into the prediction loop. Since we are not integrating, the operational and environmental variables reduce the system's ability to distinguish between a degraded battery and a battery under temporary high load (e.g., climbing a steep hill with a heavy payload). Therefore, a major research opportunity exists to develop a multimodal neural network and sensor-based that fuses multiple sensor data. The proposed system provides fault tolerance, ensures a reliable range prediction even if the electrical sensor fails or produces noisy data. This study facilitates to bridge this major gap, moving beyond ideal laboratory validations to address the stochastic nature of real-world electric mobility.

III. PROPOSED ARCHITECTURE

In this study, we have proposed a multimodal deep learning that is fault-tolerant for prediction of the SOC for a short horizon in electric vehicles. The main idea is to combine the electrical reading with the contextual features and include an adaptive fusion mechanism to include the overview features on each trip. By this, we eradicate or replace the existing system where there is a dependency on a single sensor. There are three major components in the proposed study: (i) electrical time-series modeling branch, (ii) contextual feature modeling branch, and (iii) adaptive fusion mechanism. The data pipeline is structured, and this includes the preprocessing step, sliding-window generation, and a train-test split based on the trips that prevents data leakage.

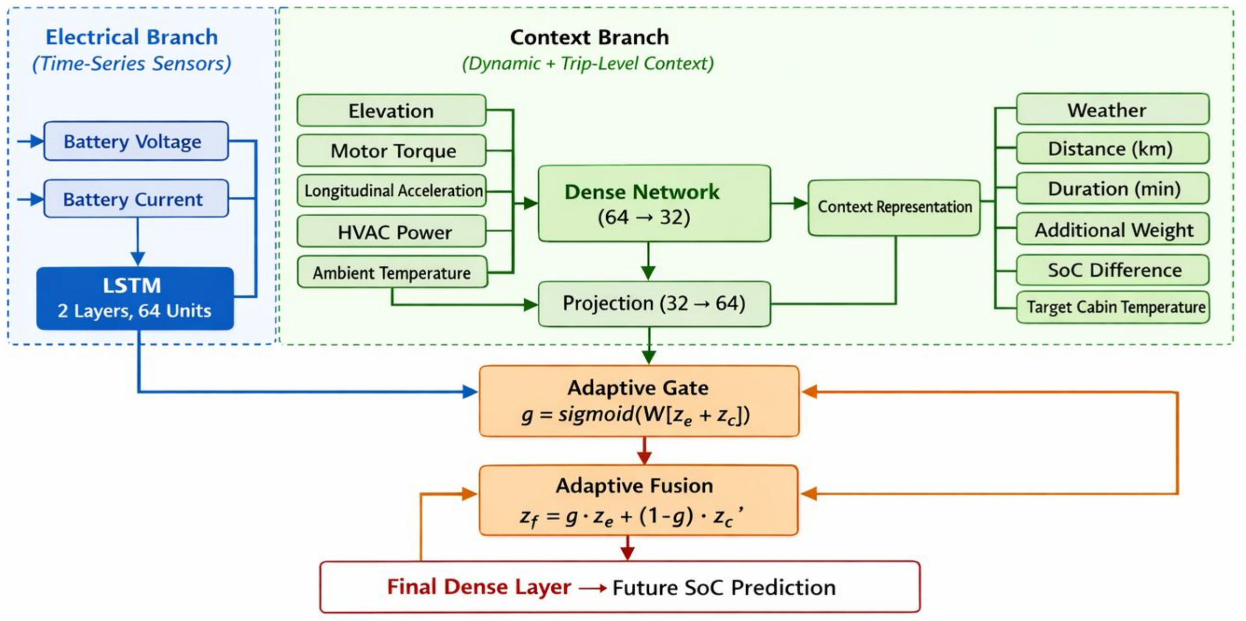

Fig. 1: System Architecture

A. Data Representation

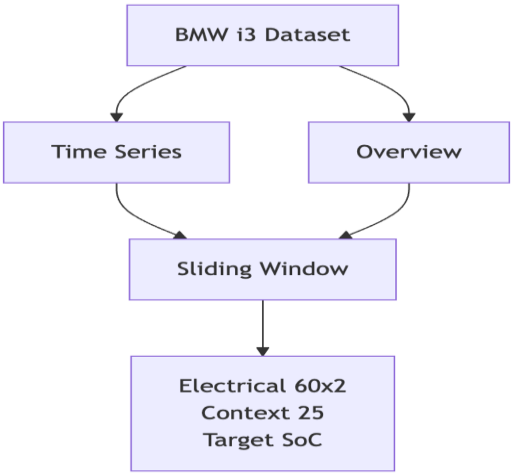

Fig. 2: Sensor data retrieval flow

This dataset consists of 70 real-world driving trips. This data is categorized into two categories of data: time-series electrical signals and trip-level contextual features.

(a) Time-Series Electrical Signals (Per Second): the primary are the voltage and the current reading from the battery. The SOC displayed during the time of the trip is recorded. Elevation of the car is also recorded in the trips and the unit is meter. Other mechanical values like motor torque, longitudinal acceleration of the car are recorded during the time of the trip. Also, majorly the power consumed by the HVAC system of the EV is tracked during the trip. Also the ambient temperature is noted in the Celsius during the time of the trip.

(b) Trip-Level Contextual Features (Static per Trip): Other contextual features are also part of this dataset, like the weather (sunny, cloudy, rainy) during the trip, which was recorded; this feature was encoded in the preprocessing step. The total distance traveled and total duration of the trip are two of the major features. There was a notes row where the extra weights carried during the trip were mentioned, which was later created as a separate feature. The SOC difference is a feature captured for a trip which is basically the difference of the initial SOC and final SOC during the trip. The Target cabin temperature and start ambient temperature are the temperature features noted for a trip.

Now to perform the supervised learning with the dataset, a sliding window strategy is configured with a window size of 60 seconds and the prediction horizon set to 60 seconds. Each of the training dataset samples consists of the electrical input where the dimension is 60 × 2 (V, I), contextual input which is a 25 dimensional vector and the target is the future State of charge at t+10.

B. Line spacing, Indent

In this division, the main aim is to process the current and voltage time-series sequence by a 2-layer LSTM network with 64 hidden units.

$$Let: X_e \epsilon R^{TX2} \tag{1}$$

The LSTM extracts temporal dynamics:

$$Z_e = LSTM\ (X_e) \tag{2}$$

The final hidden state represents the electrical embedding of the driving segment. This division captures: the voltage sags when under the load, the current spikes while the vehicle is accelerating, the behavior of the regenerative braking, and the evolution of the SOC in a short-term duration. However, this branch is vulnerable to sensor degradation, which means we are not having the right data for the sensors.

C. Equations

In this part, the system's aim is to process the contextual environment features and the static features on the trip level by a fully connected neural network.

$$X_e \in R_d \tag{3}$$

$$Z_c = f_c(X_c) \tag{4}$$

This branch models the elevation, driving behavior like torque acceleration, HVAC load, and also the trip characteristics like distance, extra weight carried and duration. The contextual features are less sensitive to individual sensor failure, unlike the electrical part and this provides an auxiliary predictive power.

D. Adaptive Fusion Mechanism

An adaptive gating mechanism is introduced to dynamically balance reliance between contextual and electrical representation. Therefore, the first important step is to match the contextual features dimensions with the dimensions of the electrical embedding.

$$Z_c' = W_p Z_c \tag{5}$$

The fusion gate is rep as:

$$g = \sigma\big(W_g[Z_e \oplus Z_c]\big) \tag{6}$$

Where: σ is the sigmoid function, and $g \in (0,1)^{64}$

The fused representation is: $Z_f = g \odot Z + (1-g) \odot Z_c'$

By this, we are allowing the model to reweight the modals dynamically based on feature reliability.

E. Robustness Enhancement via Sensor Dropout

During the training step to replicate the real-world scenarios of the sensor failures and degradation, stochastic sensor dropout is simulated. Generally, to simulate the sensor failure conditions the value of both voltage and current or either one of the values is zeroed with a predefined probability. By doing this, the model is made to learn alternative ways of prediction using other features. Also by doing this the model’s higher dependency on the electrical sensors are avoided. Along with this, the model improves generalization under degraded conditions.

F. Training Strategy

In this proposed multimodal the model is trained using MSE as the primary loss function. This allows the network to reduce the squared deviation between ground-truth future SOC values and predicted values. The performance of the model is evaluated with the Root Mean Squared Error, which is known as the RMSE value; this provides a prediction value error in normalized SOC units, which is easier to interpret. The optimization algorithm used here is the Adam optimizer as it has the feature of an adaptive learning rate mechanism and brings stability into the training of deep learning networks.

Gradient clipping is applied during backpropagation to have a stable gradient propagation through the LSTM layers and prevent exploding gradients. Using a trip-wise separation strategy, the dataset is divided, where 80% of complete trips are used for training and 20% for testing. By doing this, we are avoiding the temporal leakage between training and testing samples, and making sure the model is evaluated on entirely unseen driving scenarios.

G. *Experimental Validation*

The proposed model is evaluated in several simulated conditions to assess both robustness and accuracy. Under the normal operating conditions, firstly, the performance of the model is calculated to get the baseline predictive capability. To the electrical inputs, the Gaussian noise is injected to simulate the sensor degradation as in the real world which in turn leads to a disturbance in electrical measurements. In addition to this, we are zeroing the current input, the voltage input and both inputs simultaneously to replicate partial and complete electrical sensor failure. By this, we are introducing the controlled failure scenarios to the model.

All models fault tolerance and performance degradation is systematically evaluated using the RMSE values across all scenarios. By this proposed validation architecture, we are able to give a clear analysis of the multimodal stability in various unfavorable sensing conditions.

IV. RESULTS and DISCUSSIONS

In this proposed multimodal framework, the performance was calculated under two major conditions: the normal conditions and the failure conditions, which are simulated. The following three models were compared: (i) Baseline Multimodal Model, (ii) Dropout-Based Robust Model and (iii) Adaptive Fusion Model.

A. *Baseline Model Behavior*

TABLE-I
COMPARISON OF PERFORMANCE BETWEEN THE MODELS

Model	Normal	Gaussian Noise
Baseline	0.0398	0.0423
Dropout Model	0.0928	0.0931
Adaptive Fusion	0.0773	0.0775

In the baseline model under normal working conditions, high prediction accuracy was achieved with an RMSE value equivalent to 0.047. However, in the sensor failure conditions, the model was heavily sensitive. Voltage failure degradation is (0.334-0.0398)/0.0398 ≈438%. The key observation in this step was that the voltage failure increased RMSE by ~438%. In addition, the current failure produced a similar kind of degradation value. However, we saw significant instability in the dual sensor failure mode. The model was heavily dependent on the electrical input values like voltage and current. By this we conclude that the conventional multimodal fusion won’t reduce the robustness in the system.

B. *Effect of Sensor Dropout Training*

TABL-II
COMPARISON OF BATTERY PERFORMANCE

Model	Zero Voltage	Zero Current	Zero Both
Baseline	0.3344	0.1984	0.2044
Dropout Model	0.1085	0.0958	0.1087
Adaptive Fusion	0.1003	0.0809	0.1016

The introduction of stochastic sensor dropout during training significantly improved model stability. Voltage failure degradation is (0.1085-0.0928)/0.0928 ≈14%. The key observation in this step was the voltage failure decreased RMSE value from ~438% to 14%. In addition, there was only a minimal difference in the performance between the normal and degraded conditions. Also, we saw improved generalization across unseen trips, reducing overfitting and improving robustness. In this model majorly we observed a slight decrease in the normal-condition accuracy, but there was a large improvement in the robustness.

TABLE-III
ROBUSTNESS DEGRADATION ANALYSIS

Model	**Degradation %**
Baseline	438%
Dropout Model	14%
Adaptive Fusion	29%

C. *Adaptive Fusion Analysis*

The adaptive gating mechanism dynamically reweighted electrical and contextual embedding’s. The voltage failure degradation is (0.1003-0.0773)/0.0773 ≈29.8%. In this step, the main observations are that the model had a stabilized performance in all kinds of failure cases. This model has a structural stability for a good reliability based aware learning. Finally, the robustness, which was almost the values that we received in the dropout phase with binary failure cases.

By this, we can conclude that the improvement in the robustness was highly due to the training strategy that was undertaken, and the adaptive gating technique provides the toughness and integrity to the architecture. There was almost a 90% decrease in the catastrophic degradation in the proposed method.

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Fig. 3 compares the predicted SOC trajectories of the baseline and adaptive robust models against the ground truth. The baseline model curve shows us a perceptible drift in the upward direction, which tells us that the model is too sensitive to electrical signal fluctuations. In contrast, the adaptive robust model gives us a stable and smoother curve. From this, we can conclude that we are getting more stable predictions with less deviation compared to the true SOC.

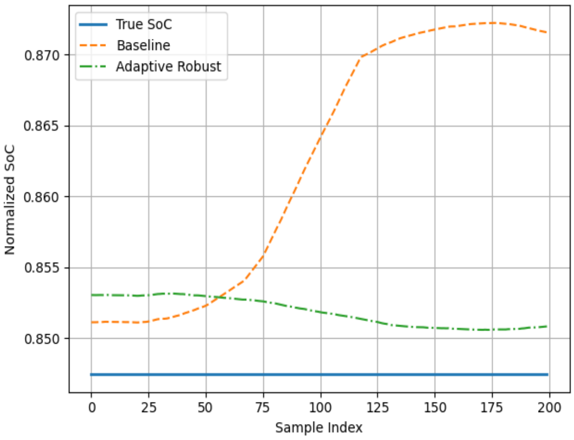

Fig. 3: Sample Index vs Normalized SOC

Figure 4 presents the absolute prediction error over time. In this graph, we are able to see the baseline model slowly increasing error towards the later samples. In contrast, the robust model has bounded error levels and this shows us the stability of the model. This demonstrates that the model predication shows lower error propagation, and this robustness-aware training effectively helped prevent the model from performing in the failed sensor failure conditions.

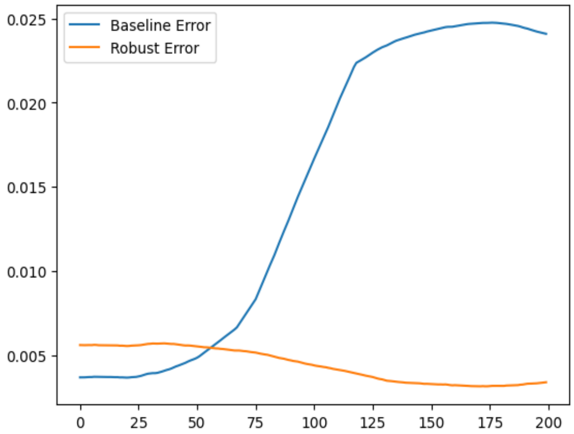

Fig. 4: Absolute Prediction Error

V. CONCLUSION

This study proposed a multimodal deep learning fault-tolerant framework to predict the State-of-Charge for short-horizon in electric vehicles. The outcomes of this study are a multimodal architecture that integrated or fuses the contextual features with the electrical features was developed. To enhance the robustness in the model sensor-dropout training was performed. Adaptive gating in the architecture enabled the dynamic reliability weighting. Performance degradation under voltage failure reduced from 438% to approximately 14%. The results demonstrate that robustness-oriented training strategies are essential for practical battery management systems operating in real-world environments.

Future works can be developed from the existing architecture in many ways. First, in this model, the sensor failures were simulated in a binary method, but instead of that, a gradual deterioration can be introduced to simulate real-world aging of the sensors, like infusing the drift, bias, and time-varying noise. Second, in this work, the adaptive gating mechanism can be improved by using the attention-based fusion, such as transformer architectures, cross-modal attention, by doing that we can introduce a dynamic and fine-grained feature weighting across time and modalities. Third, the framework can be improved to predict the Remaining Useful Life of the battery by integrating the battery health indicators and degradation modeling. In addition to these, transfer learning from different EV platforms to include different electrical modalities can be explored to validate the generalizability of the approach. Finally, the next step of progress should be real-time embedded deployment, optimizing the model for computational efficiency and integrating the model within the BMS hardware for practical field implementation.

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