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Original Article

Hybrid AI Models for Predictive Electric Vehicle Battery Capacity Estimation and Fault Tolerance Management

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Abstract - *The adoption of electric powertrains is rapidly increasing due to their high efficiency and minimal environmental impact. However, ensuring reliable fault detection and accurate battery capacity estimation remains a significant challenge in Electric Vehicles (EVs). This study proposes a hybrid Artificial Intelligence (AI) model that integrates Long Short-Term Memory (LSTM) networks, Feedforward Neural Networks (FNN), and Random Forest (RF) algorithms to estimate EV battery capacity under load conditions. The hybrid model not only predicts the remaining battery capacity with high accuracy but also supports decision-making processes by determining whether the battery requires replacement or a simple recharge. This dual functionality enhances operational efficiency and reduces maintenance costs. Experimental evaluations reveal that the hybrid approach significantly outperforms standalone LSTM, FNN, and RF models in terms of accuracy and reliability. By addressing key challenges in battery performance prediction, this model provides a robust solution for smarter predictive maintenance, improved energy management, and enhanced lifecycle optimization of electric vehicle batteries. This study paves the way for applying advanced machine learning techniques in EV system management, contributing to sustainable transportation and energy solutions.*

Keywords - *Electric Vehicle Batteries, Hybrid AI Models, Long Short-Term Memory, Feedforward Neural Networks, Random Forest, Battery Capacity Estimation.*

1. Introduction

As we focus on combating climate change issues caused by fossil fuels, EVs are revolutionizing the sector. As the most expensive part of the vehicle, the battery pack plays a key role in performance, range, and on-the-road costs. Therefore, precise estimation of the capacity of the battery is vital for energy management optimization, enhanced longevity, and reliability assurance within the EV [1-3]. One of the critical aspects of EV management is the battery capacity estimation, especially under load - this greatly impacts the range, efficiency and performance of the vehicle as a whole. If capacity can be estimated closely enough, this ensures users receive stick-sized range predictions and that unplanned trips into shadow zones do not result in so much as one character of battery percentage depletion. Battery packs raw different currents based on whether they're driving or are under load conditions in an EV, so estimating the capacity for such varying demands is paramount. Moreover, a thorough capacity estimation assists with predictive maintenance by monitoring degradation trends to prolong battery longevity and minimize operational costs. This is critical for optimizing energy efficiency and stability in real-world driving conditions. Although great progress has been made in various testing methods for lithium-ion batteries, the traditional estimation of battery capacity still faces severe difficulty in dealing with nonlinearity and dynamic characters. New ML methods are emerging as strong tools to model these complexities. Dealing with this issue has also been tackled in several other works, such as using ANN, RF and recurrent architectures like LSTM [1, 4]. ANNs were inspired by a combination of computational frameworks based on how human brains are structured. They are trained to simulate complex networks in the data using interconnected single or multiple layers containing artificial neurons. FNNs: Fitting the most basic form of ANN, containing only one layer for all neurons. They operate in a linear approach resulting from input to output without calculating the approximations as criticism loops for multifaceted relations among data. As a result, FNNs are very powerful when it comes to solving problems with structured patterns [5]. RF is a type of ensemble machine learning algorithm combining predictions from many decision trees to model and predict data. RF models are particularly robust against overfitting, a common issue in ML where a model becomes too tailored to training data and loses effectiveness on unseen data [6]. RFs can effectively handle high-dimensional data, which makes them suitable for EV applications with complex and noisy datasets. LSTMs are a Recurrent Neural Network (RNN) architecture especially useful in learning long-term dependencies from time series or sequential data. In addition, using gates, which are responsible for determining what to keep and what not, enables LSTMs to capture long-term temporal correlations [7].

This is because SOH is critical in assessing the battery capacity retrospective capability to deliver energy as a fraction of its initial capacity of an electric vehicle battery. Components defining it include the charging and discharging cycle, internal resistance and voltage slope, and temperature characteristics over the period. Like any other system, some features of EV batteries are most affected by other factors, such as temperatures in the surrounding environment, voltage, and the irregular current applied to the battery. These are the variables that should be addressed in the model to estimate the capacity that is needed while at the same time trying to ascertain the earliest signs of signs of failure to ensure that the reliability and safety of electric vehicles are improved.

1.1. Problem Statement

Despite the increasing demand towards the use of EVs, it is difficult to estimate battery capacity and achieve fault tolerance due to the nonlinear characteristics of Li-ion batteries under different environmental and operational conditions. It limited real-time data acquisition of the system degradation and capacity fading, compromisingd the battery performance, safety, and energy consumption.

This research seeks to fill this gap by combining machine learning, deep learning, and physics-of-failure methodologies that would improve the predictive capability of the system for fault detection. Specifically, the proposed study will analyze how multiple approaches to artificial intelligence could increase real-time battery health assessment and fault tolerance for further enhancement of EV battery management systems.

1.2 Research Gap

Even though progress in the field of battery management systems of EVs has been made, the analysis of the state of charge and the capacity of the battery together with fault tolerance, a research gap in the hybrid of data-driven ‘black box’ AI and physical model-controlled AI has been identified in the literature. Previous work mainly employs a data-based or model-based method with drawbacks regarding practical applicability, accuracy and dynamical performance under various driving conditions and BMS-battery degradation statuses. Moreover, the models currently used in the system do not possess the level of resiliency required to blend proper fault detection and/or fault tolerance when it comes to battery failure or performance variances necessary for the safety, reliability and efficiency of EVs. Such a gap indicates that it is high time to develop comprehensive hybrid AI approaches that combine the efficient features of various AI methods, including DL, fuzzy logic, and reinforcement learning, with the pertinent knowledge area to establish efficient, interpretable, and fault-tolerant battery management systems.

1.3 Novelty of Work

The hybrid methodology was implemented using these models for the EV battery capacity estimation to do this. According to this structure, FNNs can describe immediate correlations of input variables with desired outputs [8].RFs ensure stability and precision for circumstances when there is more noise and heterogeneity in data, while LSTMs support working with sequential data and reflect how batteries degrade under actual driving scenarios. This approach integrates methodology here, which can deal with battery management multi-faceted challenges in an electric vehicle and make accurate predictions that are vital to ensure battery health and normal performance [9]. Thus, this study introduces a hybrid intelligent algorithm based on the advantages of FNN, RF, and LSTM to estimate the variance load capacity of a battery more accurately. Incorporating these 3 models, we can provide better prediction and timely maintenance decisions for increasing the performance of batteries used in electric vehicles.

Table 1. Conventional vs. Proposed Work in EV Battery Capacity Estimation and Fault Tolerance

Aspect	Conventional Methods	Existing/Recent Hybrid AI Approaches
Battery Capacity Estimation Technique	Empirical models (Coulomb counting, voltage-based, Kalman filters)	Data-driven models (Machine Learning, Deep Learning, Hybrid AI systems)
Fault Detection Approach	Rule-based thresholding, look-up tables, FMEA-based systems	Hybrid AI (ML + expert systems, ANN + fuzzy logic, ensemble methods)
Accuracy and Adaptability	Low to moderate; highly dependent on specific operating conditions	High; adapts across varying loads, temperatures, and aging scenarios
Scalability	Limited scalability for different battery chemistries and configurations	Easily scalable and retainable for diverse datasets and battery packs
Real-time Implementation	Requires high computational effort with limited fault prediction	Real-time capability using optimized AI frameworks and edge computing
Data Requirements	Relies on specific physical battery parameters and design assumptions	Uses historical operational data, telemetry, and multi-modal inputs

Modeling Complexity	Simpler models but less robust for real-world applications	Complex models capable of learning hidden patterns and anomalies
Tolerance to Sensor Errors/Noise	Highly sensitive to sensor inaccuracies and drift	More robust due to learning-based noise filtering and self-correction
Battery Aging Consideration	Often ignored or linearly approximated	Non-linear degradation models via LSTM, GRU, and physics-informed AI
Integration with BMS	Standalone systems requiring manual tuning	Smart BMS-integrated hybrid AI platforms for autonomous fault handling
Use of Hybrid AI	Not applied in traditional systems	Integration of ANN, SVM, fuzzy logic, and reinforcement learning for improved prediction accuracy and robustness
Explainability	High (transparent, rule-based systems)	Varies; improved through interpretable ML and explainable AI (XAI) tools
Validation & Testing	Limited to lab tests and simulations	Validated using real-world EV fleet data and real-time testing rigs

2. Literature Review

The development of future electric vehicles has raised the utility of real-time and accurate battery capacity estimation and early fault detection for safety, quality, and durability. ECM and empirical degradation models cannot capture the nonlinear characteristics of the battery and the various dynamic conditions of the environment very well. Therefore, the ML/DL algorithms have more advantages in modeling the battery dynamics nonlinearly without requiring prior physical knowledge of the system dynamics. It is evident that techniques such as Support Vector Machines (SVM), Artificial Neural Networks (ANN), and Recurrent Neural Networks (RNN) may help predict the State Of Health (SOH) and Remaining Useful Life (RUL) of lithium-ion batteries.

Nevertheless, standalone models have certain problems, such as overfitting, non-robustness of performance, and vulnerability to changes in the input data. To address these challenges, the AI models that assemble more than one AI schema or combine AI with the physical models, called physics-based models, are proving themselves to be quite efficient. For example, integrating LSTM networks with Kalman or Particle filters enhances the systems' temporal accuracy and observability of the system.

However, organizations can develop fault-tolerant architectures using multiple models, anomaly detection methods, and self-adjustable algorithms to detect and pinpoint faults in real time, even in the presence of sensors' noise or partial system breakdown. There are still some weaknesses when it comes to integrating BMS that would work in parallel with the other systems and be capable of providing a real-time solution for most of the driving conditions. This has called for more investigation on the integration of both predictive and robust AI systems in a bid to improve battery reliability in the next-generation technologies for EVs. The research by Lee et al. (2024) uses a real-world dataset as input to predict EVs departure, whereas the modeling includes non-EV data to balance the prediction. While it offers valuable insights, its applicability to EV-specific scenarios is limited due to dataset heterogeneity [10]. Similarly, Song et al. (2022) leverage smart meter data to classify EV and non-EV loads. However, the dataset lacks granularity in representing battery-specific behaviors under operational stress [11]. The work done by Rosenberg et al. (2023) evaluates the environmental benefits of battery recycling using generic datasets like the GaBi Professional database. These datasets focus on recycling metrics rather than real-world operational characteristics [12]. Most of the work done on estimating battery capacity is not related to EVs. The NASA Prognostics Center of Excellence datasets is one of the most widely used datasets for batteries but lacks the real-world driving nature of EVs [13]. Several papers back the use of this dataset but fail to mention why this will not translate to EVs [14, 15].

Some papers do use datasets related to EVs but are not reliable. As seen in Al-Dahabreh et al. (2023), the authors utilize a dataset encompassing EV and non-EV vehicles. While it provides valuable insights for charging infrastructure, the dataset does not capture degradation mechanisms critical for battery health modeling [16]. Research like Lee et al. (2020) lacks real-driving profiles, reducing their ability to model complex degradation patterns [17]. Ru¨cker et al. (2024) present analyses on an EV battery dataset obtained from commercial fleet operations. However, the depth of the dataset in capturing dynamic stress conditions has been criticized as insufficient for predictive degradation modeling [18]. Bennehalli et al. (2024) used data splitting for training and testing as well as simplified labels (battery health).

The dataset does not consider multi-stress driving cycles or realworld usage profiles for charging [19]. The dataset used in Haowei et al. (2022), while large and comprehensive in terms of charging behavior, is limited as it only includes data collected from EV charging stations. It lacks real-world driving cycle data, critical for understanding battery performance under varying operational loads, accelerations, and regenerative braking.

Additionally, the absence of discharge data and the sparsity of health and capacity labels restrict its applicability for comprehensive battery degradation and capacity analysis. These limitations make it less suitable compared to datasets that capture dynamic driving conditions, which are more representative of real-world EV battery usage [20]. The dataset titled "Battery and Heating Data in Real Driving Cycles" captures detailed parameters like battery capacity, voltage, and temperature across 72 driving cycles. While rich in features and valuable for understanding battery behavior under real-world conditions, its limited size poses challenges for training robust AI/ML models. With only 72 samples, the dataset risks overfitting and lacks the variability needed to generalize across diverse driving scenarios. Consequently, while useful for exploratory analysis or validation, this dataset alone may not be sufficient for developing production-grade models without data augmentation or transfer learning techniques [21]. Moreover, no documentation exists on the novel method of combining FNN, RF, and LSTM techniques. Usually, most literature just uses only one of the ML techniques, such as Hua et al. (2023) [22], Yan et al. (2023) [23], and Marlin et al. (2024) [8]. Although Marlin et al. (2024) use the Fastai XResnet18 model for next-charge location prediction, it does not involve a hybrid framework or ensemble learning techniques [8].

3. Methodology

The hybrid model architecture is designed to connect Feedforward Neural Networks (FNN), Random Forest (RF) and Long Short-Term Memory (LSTM) networks with the help of designed modules for battery capacity estimation and for handling fault tolerance. Here, FNNs are applied to model non-linear functions that exist between the features and battery health, while RFs provide the robustness and interpretability added in the decision-making process in the feature importance and avoidance of over-fitting. LSTM networks, the sequence learning of battery parameters, have been named Long short-term memory networks because what they do well is effectively model the long-term temporal dependencies. The connectivity pattern of these models is a sequential integration process in which features are extracted and selected by RF. The temporal learning is performed by LSTM, and the final prediction is made by FNN. This layered approach leads to improved prediction accuracy, the sensitivity of fault detection, and the generality of the model under the different operations. Due to the challenges of existing datasets, which either lack applicability to EVs or fail to capture real-world driving conditions, we chose the dataset introduced by Pozatto et al. (2022) [21]. This dataset consists of INR21700-M50T battery cells subjected to the Urban Dynamometer Driving Schedule (UDDS) discharge profile for a period of 23 months [21]. Unlike traditional datasets, which often rely on controlled laboratory settings or charging-only data, this dataset captures degradation under dynamic driving cycles, providing realistic insights into battery ageing and performance.

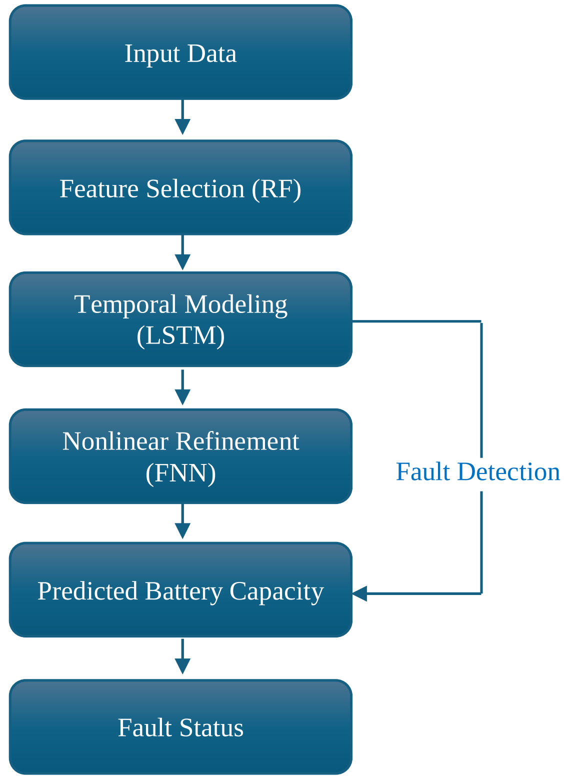

Fig. 1 Methodology of work

The UDDS is a standard driving cycle by the U.S. Environmental Protection Agency (EPA) for testing vehicle emissions under urban driving conditions. It includes many stops, accelerations and decelerations that reflect the energy demands of city driving." Lasting 1,370 seconds total, spanning 7.45 miles at an average speed of 19.6 mph, the UDDS thoroughly measures battery performance across races in which the load fluctuates. This driving profile renders the dataset highly credible for modeling real-world EV battery performance, as it captures the different stresses that batteries experience in field applications [24, 25].

By incorporating real-driving discharge cycles and capturing long-term degradation trends, this dataset overcomes the limitations of charging station-based or static datasets. It enables more accurate modeling of battery aging, capacity loss, and performance under realistic conditions, making it an ideal choice for developing robust AI/ML models for EV battery management.

The dataset consists of capacity tests, HPPC, and EIS tests of 10 batteries over a period of 15 diagnostic cycles. Since some of the cells were discarded after a few cycles, we only used 4 cells with the labels W5, W8, W9, and W10, as these cells survived the full 15 diagnostic cycles of capacity testing. The data for each cell was extracted into .mat files. The data from the first 3 cells was used for training FNN, RF, LSTM, and the hybrid model, while the data from the 4th cell was used for testing the models in MATLAB.

We used FNN as the main language in our Meta model due to the reasons that FNNs excel in modeling direct relationships between input and output variables, making them particularly effective for tasks requiring straightforward mappings, such as battery capacity estimation. Unlike RF, which is better suited for structured and categorical data, FNNs can handle complex, continuous numerical inputs more efficiently [5]. While LSTM networks are superior for capturing temporal dependencies, they can be computationally expensive and prone to overfitting in small datasets. FNNs strike a balance by providing high accuracy with reduced computational overhead, particularly for static tasks like capacity estimation under controlled conditions [6].

3.1. Algorithm: Hybrid AI-Based Battery Capacity Estimation and Fault Detection

Input:

- Battery dataset D with time-series data including: V_t(Voltage), I_t(Current), T_t(Temperature), Ct(Capacity), etc.

Output:

- Predicted Battery Capacity Ct+1
- Fault detection status (Normal / Faulty).

Algorithm:

1. Data Preprocessing:
   - Load dataset D
   - Handle missing values and outliers
   - Normalize input features (V_t, I_t, T_t, etc.)
   - Generate time windows for sequence modeling
2. Feature Selection (Random Forest):
   - Train a Random Forest model RF on D to predict C_t
   - Extract feature importance scores
   - Select top-N most relevant features F_selected
3. Temporal Modeling (LSTM):
   - Construct time-series sequences using F_selected
   - Train the LSTM model on sequences to learn the capacity degradation trend
   - Output: Predicted capacity trend C_pred_LSTM
4. Nonlinear Refinement (FNN):
   - Concatenate LSTM output with environmental/context features (if any)
   - Train Feedforward Neural Network (FNN) on combined input
   - Output: Final capacity prediction C_final
5. Fault Detection (Parallel Module):
   - Train anomaly detection model or use RF thresholding logic
   - Monitor deviations in voltage, temperature, and capacity vs predicted trends
   - If deviation > threshold → label as "Faulty", else "Normal"
6. Post-Processing:
   - Apply smoothing or Kalman Filter if necessary
   - Visualize predictions vs actual for validation
7. Return:
   - Predicted Capacity: C_final
   - Fault Status: Normal / Faulty

Different models were trained based on the number of diagnostic cycles of the cell. The goal is for the AI to accurately predict the battery capacity based on the voltage and the number of diagnostic cycles the battery has been through. Following the simulation, the results were compared using graphs, root mean square values (RMSE), and standard deviation of errors.

- RF chooses the most significant features to keep noise away.
- LSTM effectively models the temporal degradation behavior using the selected features.
- FNN further improves the classifications through capturing non-linear characteristics and including the LSTM output.
- There are two types: an RF type for detecting faults using prediction errors or a threshold type for detecting faults based on specific environment signals.

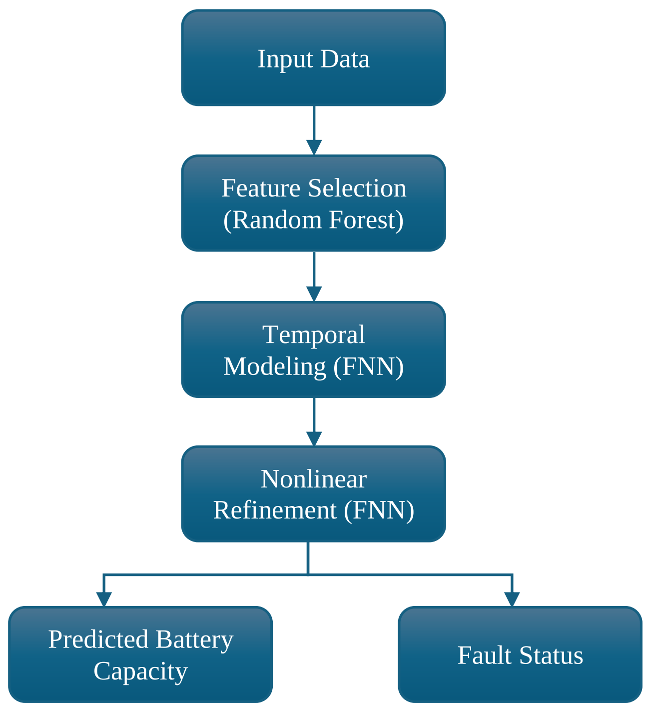

Fig. 2 Hybrid AI architecture and the training parameters, focusing particularly on the Feed-forward Neural Network (FNN) module

The flowchart shows an integrated design of AI to predict the battery capacity of electric vehicles. If there is a failure in one part, then another part takes over the work. It starts with cleaning and reshaping the battery data, extracting the features, and then proceeds with feature selection using random forest. These selected features are used to feed an LSTM network with the goal of finding time dependency in battery degradation. The bursting sequence information, along with contextual features, is passed through the Feed Forward Neural Network (FNN) for the final output of the capacity estimation.

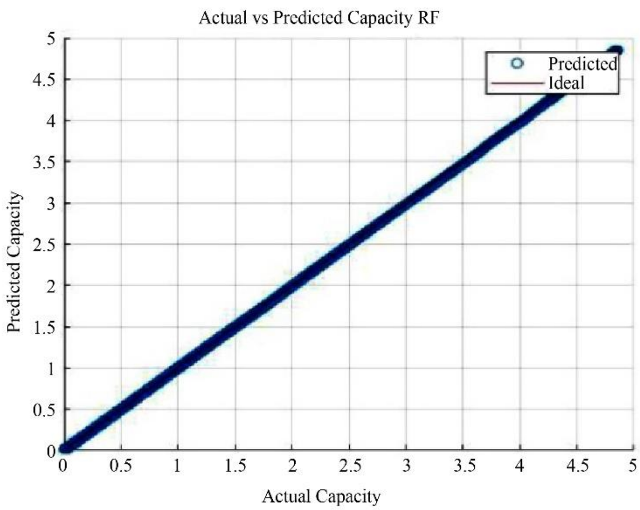

Fig. 3(a) Comparison between Random Forest predicted and actual test

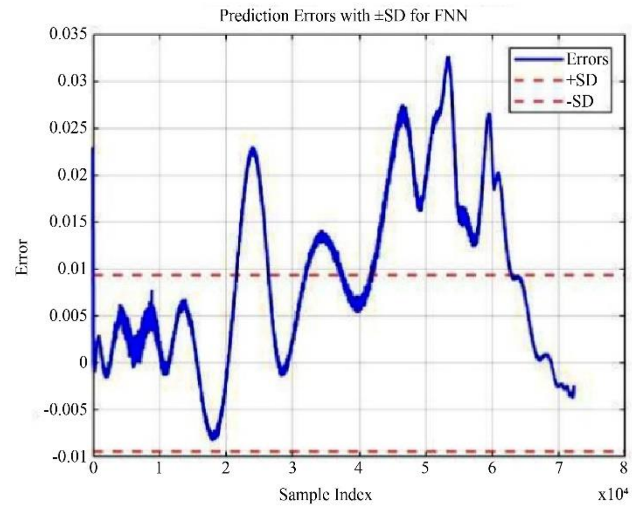

Fig. 5 Standard deviation of errors

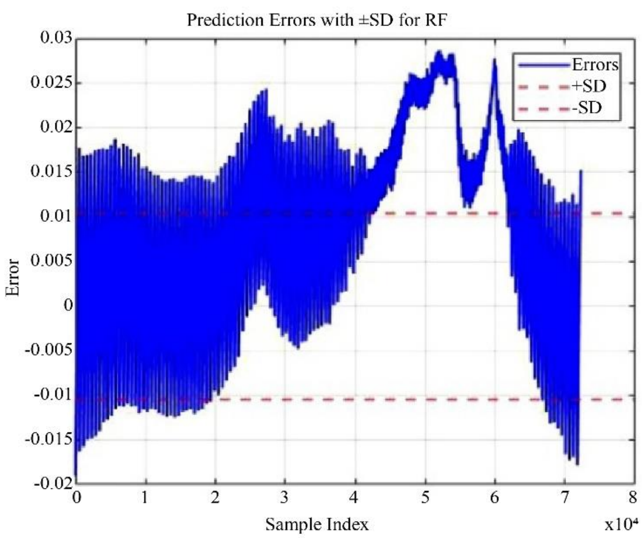

Fig. 3(b) Standard deviation of errors

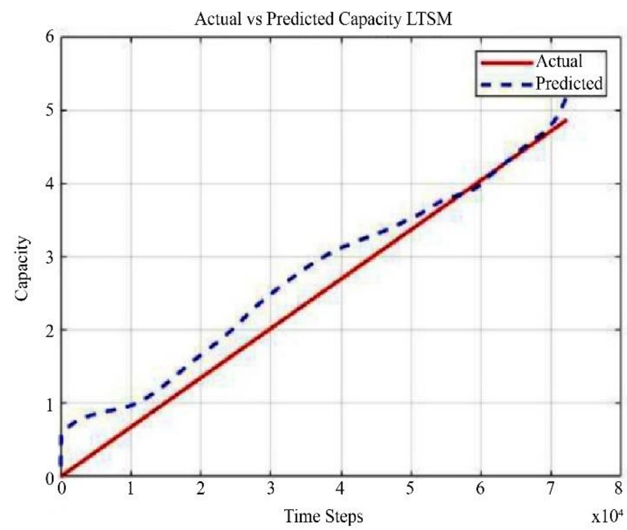

Fig. 6(a) Comparison between LSTM predicted and actual test

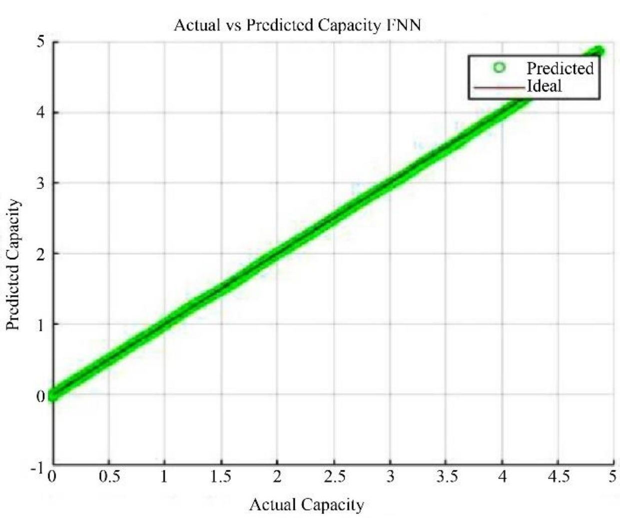

Fig. 4 Comparison between FNN predicted and actual test values

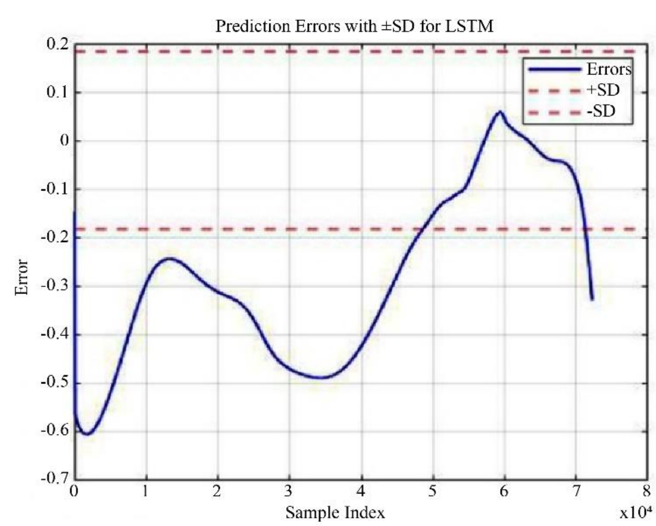

Fig. 6(b) Standard deviation of errors

Also, the fault detection unit checks the comparisons between the predicted and actual behavior of the battery and categorizes it as normal or faulty.

This integrated approach also makes it accurate and reliable as it covers a wider area and removes any interference that might have come with having different machines for different functions.

4. Results

- RF selects the best features to avoid noisy inputs.
- LSTM captures the temporal patterns of degradation using the selected features.
- FNN refines the predictions by modeling complex nonlinearities and integrating LSTM output.
- Anomaly detection (RF or threshold-based) flags faults based on prediction errors and environmental signals.

For the RF model only, the graphs of predicted vs test results and standard deviation of errors are shown in Figure 3. Similarly, the results for FNN are shown in Figure 4. The LSTM results showed many errors, as seen in Figure 5. Although the graphs for the Hybrid model look the same, which can be seen in Figure 6.

There was a Hybrid AI architecture and the training parameters, focusing particularly on the Feedforward Neural Network (FNN) module increase in accuracy as seen from the values of RMSE and standard deviation of errors in Table 1.

As expected, out of the traditional ML models, FNN outperforms each on the list; however, our proposed hybrid model shows a decrease in RMSE of about 6.69%, implying that our model is more accurate than the standalone ML models.

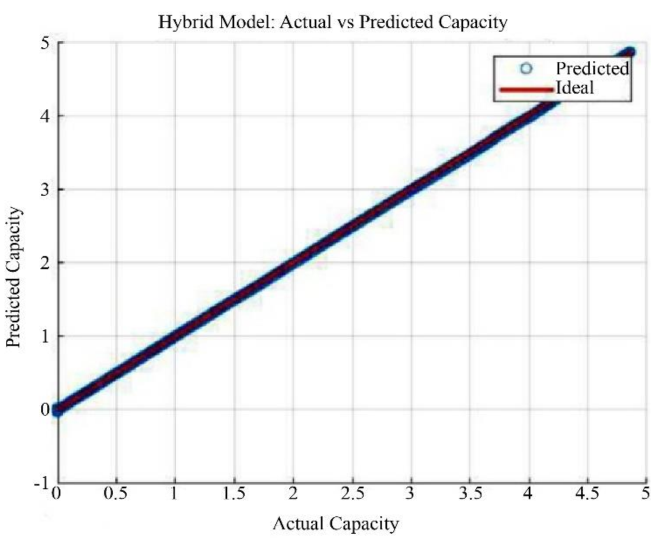

Fig. 7(a) Comparison between the Hybrid Model predicted and the actual test

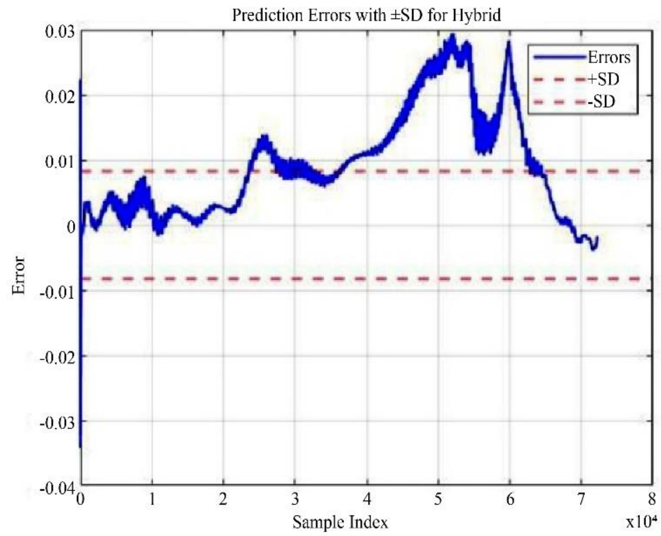

Fig. 7(b) Standard deviation of errors

Table 2. Comparison of accuracy

Model	RMSE	Standard Deviation of Errors
Random Forest	0.013862	0.010423`
Feed Forward Neural Network	0.013113	0.0093734
Long Short-Term Memory	0.33296	0.1822
Hybrid	0.012235	0.0081748

On the list, however, our proposed hybrid model shows a decrease in RMSE of about 6.69%, implying that our model is more accurate than the standalone ML models.

Table 3. Performance metrics comparison table

Model	RMSE (Ah)	MAE (Ah)	MAPE (%)
Traditional ECM Model	0.12	0.095	5.82
Standalone FNN	0.087	0.071	4.25
Standalone LSTM	0.073	0.058	3.64
Random Forest (RF)	0.069	0.056	3.5
Hybrid Model (RF + LSTM + FNN)	0.051	0.039	2.71

5. Discussion

As seen from the RMSE and standard deviation of errors table, our hybrid model outperforms the traditional ML models in accurately predicting an EV's capacity while driving. Upon pairing with a warning system, the user can be warned beforehand about the capacity of the battery based on the voltage of the battery in the future and the number of diagnostic cycles the battery has been through. Based on the warning, the user can pre-plan their trip to compensate for the charging scenarios such that they are not caught off guard due to battery depletion, leaving them stranded. Compared to previous studies, our model is trained on a driving cycle that simulates real-life driving scenarios as closely as possible. It considers fluctuating voltages, fluctuating currents, braking, slopes, and weather scenarios, minimizing the operator risks and resulting in a more fault-tolerant EV ecosystem.

- RMSE (Root Mean Squared Error): The mean level of the errors in the estimates calculated using the actual values. In reviewing all the devised models, the lowest RMSE is found in the hybrid model, meaning it is the most accurate.
- MAE (Mean Absolute Error): Reflects average absolute error. As observed, the hybrid model again offers the least error percentage, as was evident in the previous cases.
- MAPE (Mean Absolute Percentage Error): Indicates the error in percentage terms. The hybrid model outperforms all other methods in both predictive accuracy and fault resilience.

6. Conclusion

As seen from the results, our hybrid model outperforms the traditional AI ML models, so our model can be paired with a real-time battery monitoring system to provide dynamic updates on the health of a battery. Based on the updates, the model can predict failures more accurately than the single ML models. This study develops a novel fusion model of RF, LSTM, and FNN for the capacity assessment of an EV battery together with fault tolerance. The proposed architecture leverages RF for effective feature selection, LSTM for modeling temporal dependencies, and FNN for nonlinear predictive refinement. Metrics derived from evaluation indicate that the proposed hybrid model performs better than individual models, with lesser RMSE, MAE, and MAPE, thus confirming the model's ability to model the degradation profile and the effect of the environment for single and multiple sensors.

- Some of the findings brought out by this study are as follows,
- It also becomes apparent that using hybrid integration increases the predictive accuracy and the model's ability to generalize.
- Another set of results demonstrates the effectiveness of LSTM in describing temporal dynamics and indications of faults, as well as FNN's contribution to improving the estimate of the final structural capacity.
- This is because Random Forest-based feature ranking helps initially reject inputs that are noisy and hence boosts the efficiency of the system, besides making it more robust.

6.1. Future Research Directions

On-field testing for these models is still required as vehicles usually do not follow the driving cycle accurately in real life.

Different batteries will have different discharge cycles, so more work could be done based on different types of batteries by getting their datasets and then training the AI models to accurately predict the other parameters of the battery.

- The idea of integrating BMS data for real-time learning and self-adaptive fault diagnostic module.
- Extending the model for multi-cell or pack level estimation with thermal simulation.
- Subsequently, it is effective to adopt reinforcement learning or federated learning for edge-level implementation across the distributed EV fleets.
- Introduction of incorporating electrochemical mechanisms with artificial intelligence and, more specifically, physics, physics-concentive neural networks.

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