Library Progress International
Vol.44 No.3, Jul-Dec 2024: P. 23073-23078

Print version ISSN 0970 1052
Online version ISSN 2320 317X

Original Article

Available online at www.bpasjournals.com

Sensor Drift Fault Diagnostics and Control with Temporal Adaptive Range Prediction for Electric Vehicles

[1]Ravi Payal*, [2] Prof. Amit Prakash Singh

[1] Research Scholar, University School of Information, Communication & Technology, Guru Gobind Singh Indraprastha University, New Delhi, India
[2] University School of Information, Communication & Technology, Guru Gobind Singh Indraprastha University, New Delhi, India

How to cite this article: Ravi Payal, Amit Prakash Singh (2024) Sensor Drift Fault Diagnostics and Control with Temporal Adaptive Range Prediction for Electric Vehicles . *Library Progress International,* 44(3), 25076-25088

ABSTRACT: Machine learning is vital in the electric vehicle industry, but challenges remain in addressing fault diagnosis errors and range prediction inaccuracies. The "Sensor Drift Fault Diagnostics and Control with Temporal Adaptive Range Prediction" technique addresses these issues. Existing ML algorithms for fault diagnostics can cause unpredictable vehicle behavior, such as sudden acceleration or braking. The Hierarchical Iterative Proximal (HIP) Diagnostic and Control Algorithm mitigates these anomalies by accounting for sensor mounting drift. Most current range prediction techniques inaccurately estimate the battery energy consumption rate, leading to discrepancies between estimated and actual driving ranges. The Adaptive AReXo network, a novel hybrid range prediction approach, enhances range prediction in EVs by considering discharge and C-rate variability. These techniques improve the accuracy of battery energy consumption estimates and range predictions, yielding high accuracy and low RMSE in range prediction and anomaly behavior.
Keywords: Battery management system, Hierarchical Iterative Proximal (HIP) Diagnostic & Control Algorithm, Adaptive AReXo Network, C-Rate Variability.

1. INTRODUCTION

Machine learning is vital for developing and optimizing electric vehicles (EVs), as it analyzes large datasets to improve performance, efficiency, and safety [1-2]. This technology transforms EV operations by enhancing range prediction, energy management, autonomous driving, and predictive maintenance. Using data-driven algorithms, machine learning adapts to changes and makes informed decisions based on patterns. These methods optimize energy use, prevent malfunctions, boost driving performance, and enhance user experience [3]. A key application is range prediction, where algorithms analyze sensor data, driving behaviors, and environmental factors to estimate an EV's remaining range accurately, aiding drivers in planning trips and maximizing driving efficiency [4].

Machine learning algorithms optimize power distribution in EVs by considering various factors, enhancing energy efficiency, battery life, and performance [5]. These algorithms also analyze sensor data and historical records for predictive maintenance, reducing downtime and boosting component reliability. Regression models predict remaining range based on driving parameters, but their accuracy is limited due to the assumption of linear relationships, which may not capture the complex non-linear dependencies in real-world driving scenarios [6-8].

Time-series analysis techniques like ARIMA and RNNs sequentially model driving data to predict future range values, capturing temporal dependencies and short-term fluctuations. However, they may struggle with long-term variations, abrupt changes, or anomalies deviating from historical patterns. Machine learning models require extensive, high-quality training data for optimal performance; limited or poor-quality data can impair accuracy and generalizability, leading to inaccurate predictions in scenarios different from the training data. Acquiring comprehensive, representative training data for diverse driving conditions is challenging. Adapting models to real-time changes or unforeseen events is complex, necessitating further research and development of adaptive algorithms for accurate, real-time predictions [9-12].

Anomaly detection techniques utilizing machine learning identify sensor data deviations in electric vehicles (EVs), indicating potential equipment failures, but may miss rare or novel anomalies absent from training data, with effectiveness dependent on data quality and representativeness. Machine learning models classify equipment health using labeled sensor data, but accuracy relies on data quality. Prognostic models estimate remaining useful life (RUL) using regression or survival analysis based on sensor data and historical failures, with accurate RUL estimation challenged by uncertainties, degradation patterns, and changing conditions [13-15]. Enhancing range prediction and maintenance algorithms in EVs is crucial for maximizing potential, resource utilization, user experience, adoption, cost savings, safety, and sustainability, promoting a more efficient transportation system, necessitating innovative approaches for improving fault diagnosis and range prediction. The main contributions of this work are as follows:

- To analyze unpredictable and anomalous behavior in electric vehicles, a novel Hierarchical Iterative Proximal (HIP) Diagnostic and Control algorithm is employed. This algorithm utilizes the Bottom-up Logarithmic Segment Tree (BLST) to manage sensor data, the Iterative Pruned Exact Linear Time (IPELT) to verify fault detection accuracy, and the Versatile Proximal Policy (VPP) to learn from previous fault experiences.
- A novel Adaptive AReXo Network employing TNARX (Temporal Nonlinear Autoregressive eXogenous) predicts the remaining range of electric vehicles, while a regularization approach monitors predictor variables in real-time.

This paper content is developed as follows: section 2 offers the current works on literature, section 3 evaluates the working of the proposed Hierarchical iterative proximal (HIP) Diagnostic and control algorithm and Adaptive AReXo Network, section 4 deliberates the result and comparison and finally, section 5 concludes the paper.

2. LITERATURE SURVEY

Salunkhe et al [16] proposed a deep learning technique based on neural networks for energy optimization modelling in electric vehicles (EV). The pre-processed driving cycle was converted into static maps and input into a neural network for CAN bus and media control energy optimization in electric automobiles. The suggested model predicted the level of charge of the battery as well as the consumption of fuel-at-destination. The controller area network (CAN) bus is the most crucial component of an EV, and protecting it is the most challenging task. The CAN bus aberrant signals are recognized using DNN. The proposed DNN model is an integrated triplet network loss that minimizes the length of the anchor sample while also making the positive sample shorter than the negative sample. However, the limited message length adds complexity to the system and DNNs typically require a large amount of labeled training data to perform effectively.

Ullah et al. [17] proposed a metaheuristic GWO (Grey Wolf Optimization)-based ML algorithm to predict EV charging durations. Utilizing two years of actual data from Japan, the study employed three ML algorithms: ELM, FFNN, and SVR, to forecast electric vehicle charging times. To enhance model interpretability, the SHAP technique was applied to identify and quantify the most significant contributing features. The SHAP interpretations in the results section facilitated an exploratory feature analysis between charging time and other characteristics. The heater and day of the week were identified as the least sensitive input factors, while lighting conditions, season, and time of day were medium essential features. However, the study did not consider the impact of charging/discharging cycles on predicting charging time.

Bathala Prasanth et al. [18] proposed machine learning methods to improve braking energy recovery in electric vehicles and extend their range. Compared to fuzzy logic and artificial neural networks, these techniques, which considered the estimated state of charge (SOC) and brake demand, enhanced energy extraction by 59%. However, the calculations did not consider braking latency in regenerative energy.

Subhajit Chatterjee et al. [19] employed generative adversarial networks (GAN) to generate synthetic time-series data and merge it with real data, enhancing prediction accuracy. They used a single regressor model for improved forecasts and created a meta-regressor by combining multiple basic regression models in a weighted manner. An ensemble model, integrating CatBoost, Random Forest (RF), and Extreme Gradient Boosting (XGBoost), was utilized to predict daily demand. The effectiveness of the proposed methods was assessed using several markers. However, generalization errors emerged due to the complexity of managing a wide range of input variables.

Aishwarya et al. [20] developed an ML-based fault diagnosis for induction motors in both healthy and faulty states. They trained, validated, and tested algorithms, including SVM, k-NN, MLP, RF, DT, GB, XGBoost, and DL. Feature extraction and selection techniques improved model efficacy. Algorithms such as GB, XGBoost, DT, RF, k-NN, and DL achieved 98% to 100% accuracy. However, the presence of multiple simultaneous faults in the induction motor could result in fault masking.

Kosuru et al. [21] introduced an incipient bat-optimized deep residual network (IB-DRN) for detecting and classifying lithium-ion battery faults. The system collected external and internal battery data using sensors, including built-in pressure and noise sensors for precise fault isolation. The enhanced marine predators algorithm (EMPA) and sparse principal component analysis (SPCA) were utilized for feature selection and extraction, respectively. Despite improving BMS safety and reliability, the approach faced challenges in accurately isolating faults due to the complexity of interpreting multiple faults simultaneously.

Irfan Ullah et al. [22] presented a GWO-based ML algorithm for predicting EV charging times using two years of real data from Japan. The study utilized ELM, FFNN, and SVR machine learning methods, optimized through GWO, PSO, and GA metaheuristic approaches. Results showed improved model performance with these optimizers. The SHAP technique evaluated the influence of key variables on charging time, enhancing model interpretability. However, the data lacked details on user social traits, battery type, traffic patterns, charging/discharging cycles, and network topography, which significantly affect charging time.

Gao et al. [23] created a vehicle-pile-grid integrated safety evaluation system utilizing neural networks, fuzzy comprehensive evaluation, and fault tree analysis. An integrated fault tree was developed to analyze common defects during vehicle charging, forming the basis for fault detection and categorization. The evaluation indices derived from fault types formed the foundation for a comprehensive security status evaluation system. The combination of neural networks and fuzzy evaluation improves the accuracy and reliability of results, which are dependent on data quality and availability.

Fang Li et al. [24] presented a real-time voltage-based diagnostic method for lithium-ion batteries in electric vehicles. They first analyzed the causes of voltage distribution in battery cells and used kurtosis to detect cell defects. Faulty cells were then identified using multidimensional scaling and density-based spatial clustering of applications with noise after an alarm from the kurtosis-based method, which reduces the data platform's computing load. However, due to production costs and space constraints, not all battery cells are equipped with current sensors.

Zhao et al. [25] proposed a gated recurrent unit neural network-based method for multi-step voltage prediction and defect diagnosis in electric scooters. The model utilized incremental training and a dataset incorporating driver actions and vehicle status. Despite assessing correlations using the Pearson correlation coefficient, the study lacks a comprehensive evaluation of the model's robustness in real fault scenarios and adaptability to diverse environmental conditions.

According to the literature review, [16] increased system complexity and needed a lot of training data; [17] failed to account for charging and discharging cycle time; [18] neglected to account for braking latency when calculating regenerating power; [19] a huge diversity of input variables led to generalization errors; [20] fault-masking occurred as a result of multiple faults occurring at the same time; and [21] was unable to distinguish between multiple faults, which led to incorrect fault isolation.[22] data, all of which have a substantial influence on charging time, is lacking in information on user social characteristics, battery type, traffic patterns, charging and discharging cycles, and network topology.[23] To provide a foundation for analysis in the defect detection of electric vehicles, an integrated fault tree system was constructed, [24] due to production costs and space constraints, not every battery cell has a current sensor installed and [25] the model robustness in actual fault scenarios and its capacity to adjust to changing environmental conditions are not adequately captured by this research. Hence, there is a need for a novel method for overcoming errors in fault diagnosis and inaccuracies in range prediction with the existing machine learning-based approaches.

3. SENSOR DRIFT FAULT DIAGNOSTICS AND CONTROL WITH TEMPORAL ADAPTIVE RANGE PREDICTION

Electric vehicles (EVs) benefit significantly from machine learning (ML), which enhances battery management, predictive maintenance, and optimization of charging infrastructure, and aids in fault diagnostics and real-time traffic analysis. A new approach, "Sensor Drift Fault Diagnostics and Control with Temporal Adaptive Range Prediction," improves anomaly detection and control. Traditional ML algorithms for fault diagnostics can cause unpredictable vehicle behavior due to sensor drift from chassis vibration. To address this, a Hierarchical Iterative Proximal (HIP) Diagnostic and Control Algorithm detects anomalies in variables like power consumption rate, battery SoC, temperature, voltage, charging/discharging current, and motor speed/torque, accounting for sensor drift. Current range prediction methods often inaccurately estimate battery energy consumption, causing discrepancies between predicted and actual driving ranges. To correct these errors, a Hybrid Range Prediction approach, the Adaptive AReXo Network, uses real-time telemetry data such as battery SoC, temperature, voltage, charging/discharging current, vehicle speed, motor speed, tire pressure, and ambient conditions to affect the discharge profile and C-rate variability. Architecture of Sensor Drift Fault Diagnostics and Control with Temporal Adaptive Range Prediction for Electric Vehicles is shown in Figure 1.

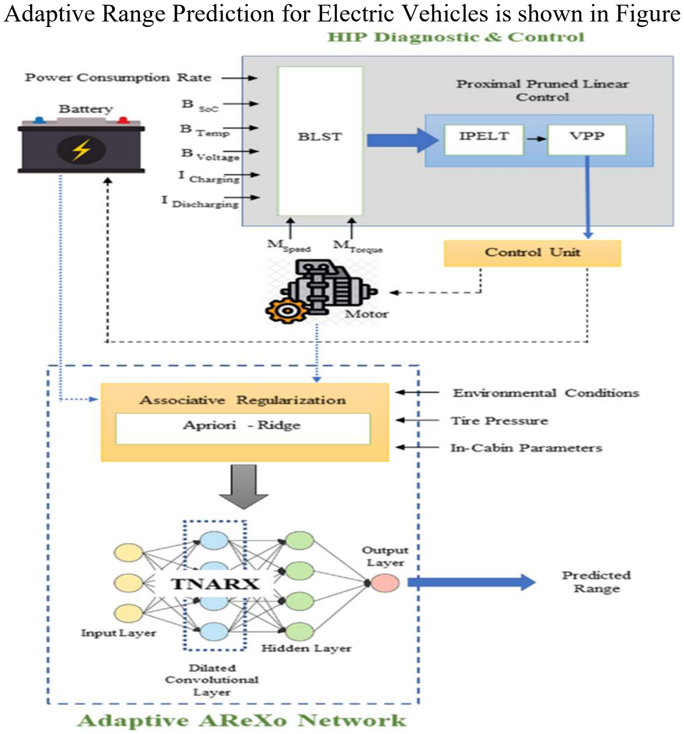

Figure 1. Architecture of Sensor Drift Fault Diagnostics and Control with Temporal Adaptive Range Prediction for Electric Vehicles

The Hierarchical Iterative Proximal (HIP) Diagnostic & Control Algorithm, employing the Bottom-up Logarithmic Segment Tree (BLST) and Iterative Pruned Exact Linear Time (IPELT) algorithms, detects anomalies in input variables and addresses sensor drift. The Versatile Proximal Policy (VPP) Optimization updates its policy based on prior faults. The Adaptive AReXo Network, utilizing a Temporal Nonlinear AutoRegressive eXogenous (TNARX) Network, predicts the electric vehicle's remaining range. The Associative Regularization approach, combining Apriori associative rule and Ridge regularization, enables real-time monitoring of predictor variables, capturing discharge profile and C-Rate variability, reducing errors in energy consumption rate estimation. The "Sensor Drift Fault Diagnostics and Control with Temporal Adaptive Range Prediction" method addresses range prediction and fault detection issues using these proposed machine learning approaches.

3.1 Hierarchical Iterative Proximal (HIP) Diagnostic & Control Algorithm

Existing machine learning (ML) algorithms for fault diagnostics often exhibit unpredictable and abnormal vehicle behaviors. To address these issues, a novel Hierarchical Iterative Proximal (HIP) Diagnostic & Control Algorithm has been introduced. Current fault diagnostic methods fail to fully consider unexpected behaviors like sudden acceleration, braking, or handling due to the non-linear interaction of multiple components and the cascading effects of sensor mounting drift from chassis vibration. This method focuses on identifying abnormalities in critical input variables such as power consumption rate, battery temperature, voltage, State of Charge (SoC), charging and discharging current, motor speed, and torque, aiming to improve fault diagnosis by addressing variations in these parameters, particularly considering sensor mounting drift. This novel Fault Diagnostic & Control approach includes techniques like BLST (Bottom-up Logarithmic Segment Tree), IPELT (Iterative Pruned Exact Linear Time) algorithm and VPP (Versatile Proximal Policy) which will be explained in further sections.

3.1.1 BLST (Bottom-up Logarithmic Segment Tree)

The BLST Algorithm is a sophisticated fault diagnosis method that efficiently handles sensor data using a segment tree. This hierarchical framework facilitates systematic data analysis and effective range inquiries. Its bottom-up architecture ensures speed and scalability, making it ideal for real-time applications. By recursively segmenting the sensor data, this structure provides a methodical approach to analysis and efficient range inquiries. The BLST (Bottom-up Logarithmic Segment Tree) Algorithm provides a step by step depiction of its effective hierarchical structure and processing logic by demonstrating the sequential stages involved in handling sensor data and identifying anomalies.

Algorithm 1. BLST (Bottom-up Logarithmic Segment Tree)

Input : Real-time sensor data.
Output : Exploit the algorithm design for real-time monitoring, ensuring prompt detection of anomalies or errors in sensor data.

STEP 1 - **Segmentation:**
Recursively divide the sensor data using the segment tree structure.

STEP 2 - **Leaf Node Representation:**
Represent individual data points or brief intervals of real-time sensor measurements at the leaf nodes.

STEP 3 - **Comparison of Real-time and Parent Node Data:**
For each leaf node, compare its direct sensor data with the standard deviation of the data stored in the corresponding parent node. Detect sudden changes in sensor measurements, indicating sensor mounting drift.

STEP 4 - **Bottom-Up Construction:**
Build the segment tree in a bottom-up fashion, starting from the leaves and progressing towards the root.

STEP 5 - **Range Query Efficiency:**
Utilize the segment tree hierarchical structure for efficient range queries. Enable quick detection of anomalous patterns or deviations within specified data ranges.

STEP 6 - **Statistical Characteristics for Anomaly Detection:**
Use predefined criteria based on statistical measurements (mean, standard deviation) for anomaly detection.

BLST technique segments data using a hierarchical tree to detect sensor mounting drift, comparing leaf nodes with parent nodes. This method identifies deviations in specified ranges by constructing the tree bottom-up and efficiently querying ranges for rapid anomaly detection based on statistical features like mean and standard deviation. By iteratively eliminating unnecessary nodes, the IPELT algorithm improves efficiency and speeds up data analysis for precise anomaly identification in dynamic sensor environments, which will be explained in a further section.

3.1.2 IPELT (Iterative Pruned Exact Linear Time) algorithm

The Iterative Proximal Extreme Learning Tree (IPELT) algorithm improves fault diagnostics by using an iterative statistical criterion to identify abnormalities from both mounting and component failures. Through repeated linear iterations, it enhances fault detection for these irregularities. Upon detection, the algorithm corrects the issues, restoring normal system operation while handling complex non-linear data exchanges. Algorithm 2 presents the IPELT algorithm. Its strength lies in iteratively refining detection results, ensuring the accuracy of identified anomalies. Statistical measurements and iterative processes help distinguish real issues from false positives, proving invaluable for electric vehicle fault diagnostics.

Algorithm 2. Iterative Pruned Exact Linear Time (IPELT) Algorithm

Input : • Real-time sensor data
• System parameters
• Threshold for fault detection
Output : • Fault diagnostic report
• Corrective actions for fault rectification

Algorithm Steps:

STEP 1 - **Initialization:**
Initialize the IPELT algorithm.
STEP 2 - **Iterative Fault Detection:**
Apply the iterative statistical criterion to assess fault detection. Evaluate statistical measures to distinguish anomalies arising from mounting failure and component failure.
STEP 3 - **Mitigation of Non-linear Data Interaction:**
Mitigate non-linear data interaction between different components. Address complex relationships and interactions by reducing non-linearities in the data.
STEP 4 - **Fault Identification:**
Once anomalies are detected and distinguished, identify faults based on predefined criteria.
STEP 5 - **Fault Rectification:**
When a sensor drift fault is identified, a fault rectification algorithm is triggered to correct the impact of the faulty sensor readings. The algorithm was involve adjusting the sensor readings, applying a correction factor, or selectively excluding the faulty data points. To get things back to normal, adjust things like battery capacity, charging time, and charging speed. These changes are intended to maximize system performance and address any problems that have been found during fault analysis.
STEP 6 - **Fault Diagnostic Report:**
Generate a fault diagnostic report based on the outcomes of the iterative fault detection process.

The IPELT methodology is an algorithm for real-time sensor data processing and defect detection. It initializes, iteratively evaluates faults using statistical criteria, addresses non-linear data interactions, identifies faults, rectifies sensor drift faults with adjustment algorithms, and produces a comprehensive fault diagnostic report with remedial action suggestions. Integration with Versatile Proximal Policy (VPP) Optimization enhances optimization capabilities and accelerates error detection and correction. The fault diagnostic report, detailed in the following section, supports decision-making for system maintenance and improvement by offering insights into diagnosed defects.

3.1.3 VPP (Versatile Proximal Policy) Optimization

VPP Optimization, a fault diagnostic technique, enhances system error response through dynamic learning, continuously refining fault-handling strategies based on past errors. It generates post-diagnosis control measures, such as temperature regulation and power distribution adjustments, and devises safety procedures, including component shutdowns or emergency actions, in extreme cases. The step by step algorithm of Versatile Proximal Policy (VPP) Optimization is depicted as Algorithm 3 below. The algorithm's adaptive control actions and learning capabilities make it valuable for fault management in electric vehicles.

Algorithm 3. Versatile Proximal Policy (VPP) Optimization Algorithm

---

Inputs:
- Sensor data from Electric Vehicles
- Historical data for fault analysis
- Temporal adaptive range predictions
- Control parameters

Outputs:
- Optimized control policies
- Fault diagnostic information

STEP 1- **Initialization:**
Initialize the VPP algorithm parameters and set initial control policies.
STEP 2- **Data Collection:**
Acquire sensor data from Electric Vehicles, historical data for fault analysis, and temporal adaptive range predictions.
STEP 3- **Temporal Adaptive Range Prediction:**
Utilize historical data and machine learning techniques to predict temporal adaptive ranges for sensors.
STEP 4- **Fault Detection:**
Implement fault detection mechanisms using the VPP algorithm to identify sensor drift and other faults in real-time.

STEP 5- **Proximal Policy Optimization:**
Apply the VPP algorithm to optimize control policies based on the detected faults and adaptive range predictions.
STEP 6- **Control Adjustment:**
Adjust control parameters, such as battery capacity, charging time, and speed, based on optimized policies and fault diagnostics.
STEP 7- **Real-time Monitoring:**
Continuously monitor sensor data and system performance in real-time.
STEP 8- **Adaptive Learning:**
Incorporate adaptive learning mechanisms within the VPP algorithm to enhance fault detection and control optimization over time.
STEP 9- **Feedback Loop:**
Establish a feedback loop to iteratively refine control policies and fault diagnostic capabilities based on ongoing sensor data and system performance.
STEP 10- **Output Generation:**
Generate optimized control policies and detailed fault diagnostic information.

The algorithm commences with data collection, fault detection, and temporal adaptive range prediction. Proximal Policy Optimization refines control policies using these predictions and detected faults, resulting in adjusted control settings and real-time monitoring. An iterative feedback loop improves control optimization and fault detection through adaptive learning, providing comprehensive fault diagnostics and optimal control rules. This algorithm accommodates diverse fault types. The following section introduces the Adaptive AReXo Network, an innovative approach for improving range prediction.

3.2 Adaptive AReXo Network

A novelty named the Adaptive AReXo Network makes use of real-time telemetry data to precisely estimate the driving range of electric vehicles and predict battery energy consumption rates. With the use of this creative method, Discharge Profile and C-Rate Variability are captured, providing more precise insights into battery condition. This novel Adaptive AReXo Network approach includes techniques like Associative Regularization approach and TNARX (Temporal Nonlinear AutoRegressive eXogenous) Network which will be explained in further sections.

3.2.1 Associative Regularization approach

The Adaptive AReXo Network incorporates Associative Regularization, merging Apriori associative rule with Ridge regularization for real-time predictor variable monitoring. It detects patterns in battery SoC, voltage, temperature, motor speed, and power consumption through association rule mining. This method boosts electric vehicle performance and accuracy in energy consumption estimates. Algorithm 4 shows steps of the Associative Regularization Algorithm, highlighting its role in optimizing energy management, productivity, and battery lifespan in dynamic settings.

Algorithm 4. Associative Regularization Algorithm

Input: • Predictor variables (features)
• Discharge profile data
• C-rate data
• Energy consumption rate estimation
Output: Stabilized parameters for reduced sparsity
Algorithm Steps:
STEP 1 - **Initialization:**
Initialize the Associative Regularization approach.
STEP 2 - **Association Rule Mining with Apriori:**
Utilize the Apriori algorithm for association rule mining. Identify inter-relationships among power consumption rate, battery SoC, Battery temperature, Battery Voltage, Charging and discharging current, Motor Speed and torque to capture discrepancies in discharge profile and C-rate.
STEP 3 - **Association Rule Identification:**
Identify significant association rules characterizing relationships among predictor variables.

STEP 4 - **Ridge Regularization:**
Apply Ridge regularization to capture and stabilize relationships identified by association rules. Stabilize parameters to reduce sparsity in the data.
STEP 5 - **Real-time Monitoring:**
Continuously monitor predictor variables in real-time. Dynamically adjust regularization parameters based on evolving data.
STEP 6 - **Capture Discharge Profile Variation:**
Leverage association rules and Ridge regularization to effectively capture variation in the discharge profile.
STEP 7 - **Capture C-rate Variation:**
Capture variation in C-rate by utilizing established relationships among predictor variables.
STEP 8 - **Error Reduction in Energy Consumption Rate Estimation:**
Utilize stabilized parameters from Ridge regularization to reduce errors in energy consumption rate estimation.
STEP 9 - **Adaptive Model Adjustment:**
Dynamically adjust the model based on evolving relationships among predictor variables.

This method combines Ridge regularization for parameter stabilization with association rule mining to uncover complex interrelationships, dynamically adjusting the system in real-time to capture fluctuations in critical electric vehicle parameters. It significantly reduces inaccuracies in energy consumption rate calculations. The Associative Regularization method, paired with the TNARX (Temporal Nonlinear AutoRegressive eXogenous) Network, enhances monitoring and estimation accuracy in real-world electric vehicle applications. The TNARX Network further improves the algorithm's ability to assess and predict energy usage patterns by simulating complex temporal correlations, as detailed in a later section.

3.2.1 TNARX (Temporal Nonlinear AutoRegressive eXogenous) Network

TNARX Network is essential for evaluating a remaining range of the electric vehicle since it takes into description several predictor variables from the C-rate and dynamic discharge profile. With a dilated convolution layer placed after the NARX input layer, range prediction accuracy is increased by capturing sequential dependencies in telemetry data over long periods of time. This improvement lowers the estimation error in battery energy consumption rate, improving the accuracy of range prediction by addressing the discharge profile and C-rate and decreasing sparsity and indiscretion in telemetry data.

The Adaptive AReXo Network's Neural Network architecture utilizes a recurrent layer to capture temporal dependencies by integrating previous input and output data. The input layer consists of discharge profile and C-rate characteristics, while hidden layers with nonlinear activation functions extract complex patterns. The output layer predicts critical metrics such as the remaining range of electric vehicles. Training involves adjusting connection weights to minimize differences between expected and actual range values. A dilated convolution layer enhances the understanding of long temporal relationships, and the Adaptive AReXo network addresses sparsity issues and reduces estimation errors in battery energy consumption rate.

The proposed method addresses anomalies and sensor drift, enhancing electric vehicle range estimation's accuracy and reliability. It employs advanced fault detection to swiftly identify irregularities, improving efficiency and safety, and employs calibration to correct sensor drift, guaranteeing data integrity. This method aims to refine algorithmic precision and reduce battery consumption estimation errors by factoring in driving conditions and battery status. Its primary goals include optimizing efficiency, diagnostics, driver confidence, and prediction accuracy. The effectiveness of these techniques is evaluated in Section 4.

4. RESULT AND DISCUSSION

This section presents the outcomes derived from the proposed model. The findings demonstrated that the proposed model reduced anomaly errors and extended the battery life cycle. Additionally, a comparison of the suggested approach range prediction accuracy with other methods already in use supports its claims. Tools and system specification, simulation result, performance evaluation, comparison evaluation is discussed in the further section.

4.1 Tool & System Specification

- Software : MATLAB
- OS : Windows 10 (64-bit)
- Processor : Intel i5
- RAM : 8GB RAM

4.2 Simulation result

This section describes the simulation result of the proposed method. The circuit diagram of the Controller and sensor dynamic and Lateral vehicle dynamics is shown in Figure 2.

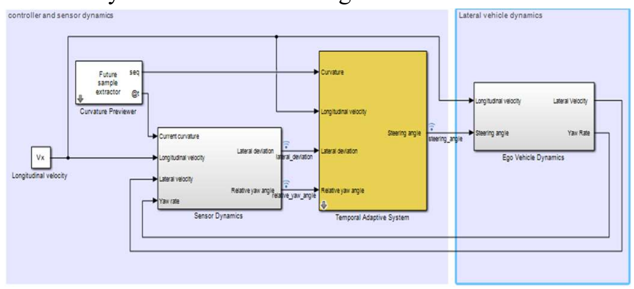

Figure 2. Overall Simulated view of Controller and Sensor dynamic and Lateral vehicle dynamics of the proposed model

The suggested method controller and sensor dynamics as well as the lateral vehicle dynamics are shown in Figure 2. Longitudinal velocity is used to pass via the Sensor Dynamics, Temporal Adaptive System, Eco vehicles of the Controller, and Sensor Dynamics. The temporal adaptive system is the primary means by which the controller functions and transfers velocity to the sensor dynamics in order to estimate the range prediction. This longitudinal velocity controls every step of the sensor dynamics process.

The circuit involves a dynamics model that takes inputs such as longitudinal velocity, lateral velocity, and yaw rate. These parameters influence the lateral deviation and relative yaw angle of the vehicle. The expression $\frac{1}{s}$ represents an inverse relationship, possibly a time constant or frequency parameter. The combination of control inputs $(u(1) * u(3) + u(2))$ suggests a linear combination influencing the dynamics. In essence, this circuit represents the interconnected relationships between the vehicle motion parameters and control inputs, providing a framework for understanding and potentially designing a control system for the vehicle behaviour on the road.

4.3 Performance Evaluation

The performance Evaluation of the proposed model in the unpredictable and anomalous vehicle behavior and Range prediction based on achieved outcome is explained in detail in this section.

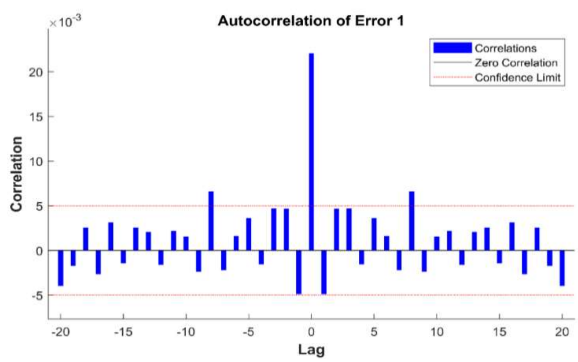

Figure 3. Correlation in the proposed mode

Figure 3 illustrates the variation of Correlation with positive and negative lag of the proposed model. In correlation analysis, "lag" indicates the time offset between two variables. Positive lags imply delays; negative lags indicate leads influencing correlation values. When the lag is -20 it achieves the Correlation -4×10^{-3}, and while the lag is -19, it achieves the maximum Correlation of -2×10^{-3} with the use of Hierarchical Iterative Proximal (HIP) Diagnostic & Control Algorithm.

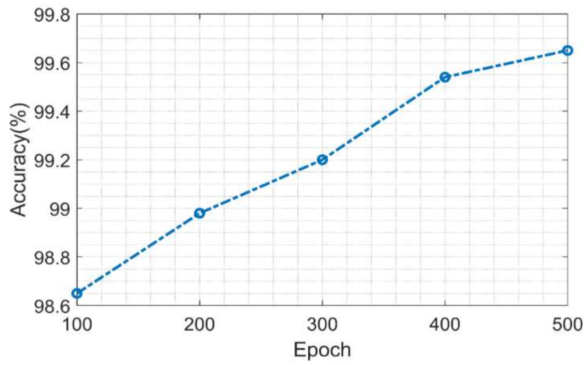

Figure 4. Accuracy (%) in the proposed model

Figure 4 illustrates the Accuracy (%) of the proposed model. When the epoch is 100 it achieves the Accuracy (%) is 98.65, and while the epoch is 200 it achieves the Accuracy (%) of 98.99. Here when the epoch increases, Accuracy (%) value also increases. With the help of the Associative Regularization approach used in the proposed method, the range prediction accuracy is improved.

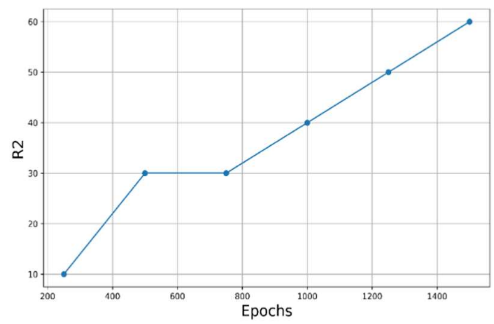

Figure 5. R^2 (coefficient of determination) in the proposed model

The proposed model R^2 (coefficient of determination) is shown in Figure 5. At 250 epochs, the R^2 is 10, and at 500 epochs, the R^2 is 30. In this case, the R^2 value similarly increases as the epoch does. The proposed method Associative Regularization technique helps to increase the coefficient of determination in range prediction.

4.4 Comparison of Proposed Model with Previous Models

This section highlights the proposed method performance by comparing it to the outcomes of existing approaches and showing their results based on various metrics such as accuracy, precision, recall and RMSE.

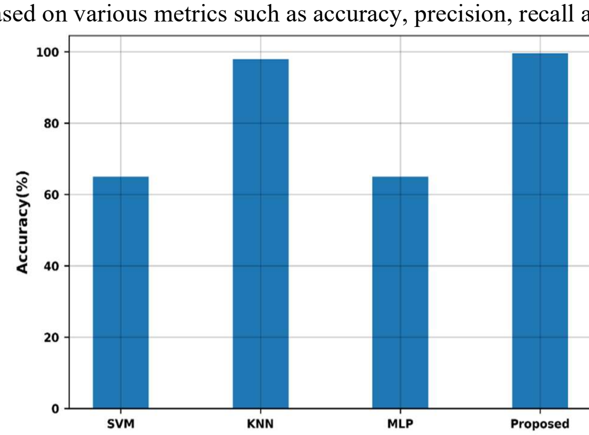

Figure 6. Comparison of Accuracy in Range prediction in the proposed model

Figure 6 depicts the comparison of the accuracy in Range prediction of the proposed model with other existing approaches. The accuracy of the proposed approach is compared with existing techniques such as SVM, KNN, MLP [26]. The accuracy of the proposed model obtains the value of 99.6% whereas the accuracy of SVM, KNN and MLP are 65%, 98.6% and 65% respectively.

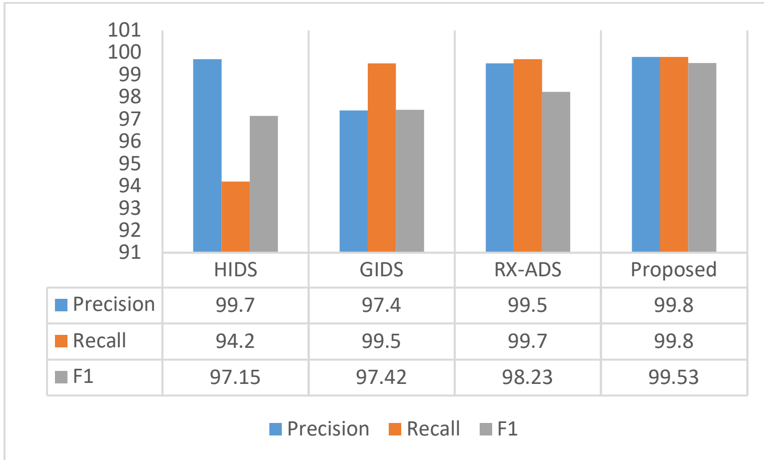

Figure 7. Comparison of Precision, Recall and F1 with existing techniques

Figure 7 depicts the comparison of the Precision, recall and F1 of the proposed model with other existing approaches. The Precision of the proposed approach is compared with existing techniques such as HIDS, GIDS, RX-ADS [27]. The Precision of the proposed model obtains the value of 99.8% whereas the Precision of HIDS, GIDS, RX-ADS are 99.7%, 97.4%, 99.5% respectively. By Adaptive AReXo Network method the range prediction has improved.

The Recall of the proposed approach is compared with existing techniques such as HIDS, GIDS and RX-ADS [27]. The Recall of the proposed model obtains the value of 99.8% whereas the Recall of HIDS, GIDS and RX-ADS are 94.2%, 99.5% and 99.7% respectively. The recall of the proposed model is high whereas the HIDS is low.

The F1 measurements of the suggested strategy are compared to those of well-established techniques including HIDS, GEDS, and RX-ADX [27]. F1 measure for the proposed model is 99.53%, whereas HIDS, GEDS, and RX-ADX have the values of 97.15%, 97.42%, and 98.23%, respectively. The F1 measures in range prediction of the proposed model is high, whereas the F1 measures in range prediction of HIDS is poor.

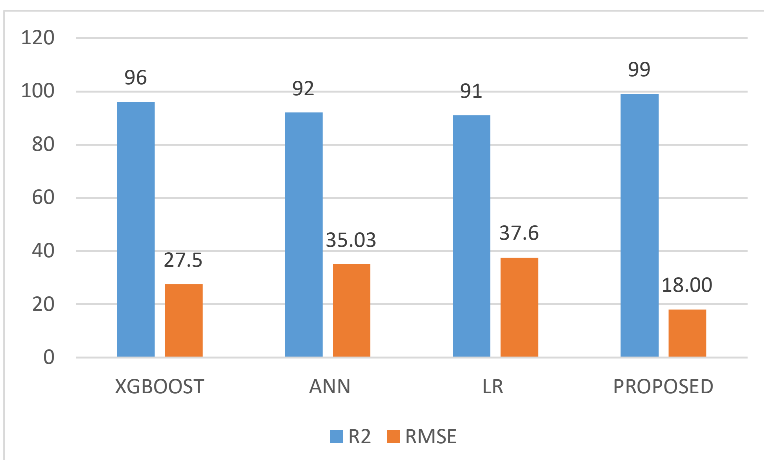

Figure 8. Comparison of R2, RMSE and MAE with existing techniques

The comparison between R2, RMSE and MAE with other current methods of the proposed model is shown in Figure 8. The proposed approach RMSE is contrasted with those of established methods as XGBOOST, ANN, and LR [27]. The suggested model root mean square error (RMSE) is 18%, while the corresponding values for XGBOOST, ANN, and LR are 27.5%, 35.03%, and 37.6%, respectively. The error has been reduced using the Associative Regularization approach.

The R^2 (coefficient of determination) of the recommended approach is contrasted with those of established methods such as lightGBM, XGBOOST, ANN, and LR. The proposed model R^2 (coefficient of determination) is 0.99%, while the values for lightGBM, XGBOOST, ANN, and LR are, respectively, 0.98%, 0.96%, 0.92%, and 0.91%. When it comes to range prediction, the proposed model R^2 (coefficient of determination) is high while LR R^2 (coefficient of determination) is low.

The MAE of the proposed strategy is compared to that of well-known techniques, including lightGBM, XGBOOST, ANN, and LR. The values for lightGBM, XGBOOST, ANN, and LR are 14%, 21.8%, 25%, and 25.3%, respectively, while the MAE of the proposed model is 12.5%. Regarding range prediction, the MAE of the proposed model is low with better prediction, but the MAE of LR is significantly high.

Overall, the suggested approach outperforms the current approaches; only 18% of root mean square error and 12.5% of MAE occur in the proposed model. The Accuracy, recall, precision, F1 measures and R^2 of the suggested model are 99.6%, 99.8%, 99.6%, 99.53% and 0.99% respectively, in line with the accuracy of the suggested technique. In comparison to the current approach, the suggested strategy yields favorable results. Thus, there is low RMSE and MAE in fault diagnostics and high accuracy, recall, precision, R^2 and F1 measures in range prediction in the proposed method.

5.CONCLUSION

The Electric Vehicle Battery Maintenance System (BMS) employs the Hierarchical Iterative Proximal (HIP) Diagnostic & Control Algorithm to detect battery pack anomalies, considering parameters like battery temperature, voltage, charging/discharging current, motor speed, and torque to correct sensor drift. The Adaptive AReXo Network enhances range prediction by integrating real-time telemetry data variations, including battery state of charge (SoC), temperature, voltage, current, capacity fade, vehicle speed, motor speed, torque, environmental conditions, tire pressure, and in-cabin parameters. This model achieves 99.6% accuracy, outperforming SVM, KNN, and MLP in accuracy, precision, recall, and RMSE. Its range prediction precision and recall are 99.8%, and RMSE is 38.7%, exceeding existing methods. Furthermore, its anomaly detection precision surpasses HIDS, GIDS, and RX-ADS. The proposed technique delivers exceptional performance, providing a robust solution for range prediction and anomaly detection in electric vehicle batteries, with superior accuracy, precision, and recall, effectively addressing prediction errors and charge balancing challenges.

REFERENCES

[1] Zahedi R, hasan Ghodusinejad M, Aslani A and Hachem-Vermette C (2022) Modelling community-scale renewable energy and electric vehicle management for cold-climate regions using machine learning. Energy Strategy Reviews 43:100930.

[2] Mazhar T, Asif RN, Malik MA, Nadeem MA, Haq I, Iqbal M, Kamran M and Ashraf S, (2023) Electric Vehicle Charging System in the Smart Grid Using Different Machine Learning Methods. Sustainability 15(3):2603.

[3] Ullah I, Liu K, Yamamoto T, Zahid M and Jamal A (2023) Modeling of machine learning with SHAP approach for electric vehicle charging station choice behavior prediction. Travel Behavior and Society 31:78-92.

[4] Roy A and Law M (2022) Examining spatial disparities in electric vehicle charging station placements using machine learning. Sustainable cities and society 83:103978.

[5] Khan SA, Eze C, Dong K, Shahid AR, Patil MS, Ahmad S, Hussain I and Zhao J (2022) Design of a new optimized U-shaped lightweight liquid-cooled battery thermal management system for electric vehicles: A machine learning approach. International Communications in Heat and Mass Transfer 136:106209.

[6] Bas J, Zou Z and Cirillo C (2023) An interpretable machine learning approach to understanding the impacts of attitudinal and ridesourcing factors on electric vehicle adoption. Transportation Letters 15(1):30-41.

[7] Balaiah G, Dhanasree VP, Jyothi M, Varun K and Chowhan D (2022) Predicting Charge Consumption of Electric Vehicles Using Machine Learning. Journal of Algebraic Statistics 13(3).

[8] Mądziel M and Campisi T (2023) Energy Consumption of Electric Vehicles: Analysis of Selected Parameters Based on Created Database. Energies 16(3):1437.

[9] Li R, Hong J, Zhang H and Chen X (2022) Data-driven battery state of health estimation based on interval capacity for real-world electric vehicles. Energy 257:124771.

[10] Shen H, Wang Z, Zhou X, Lamantia M, Yang K, Chen P and Wang J (2022) Electric Vehicle Velocity and Energy Consumption Predictions Using Transformer and Markov-Chain Monte Carlo. IEEE Transactions on Transportation Electrification 8(3):3836-3847.

[11] Zhao J, Ling H, Liu J, Wang J, Burke AF and Lian Y (2023) Machine learning for predicting battery capacity for electric vehicles. ETransportation 15:100214.

[12] Zahedi R, hasan Ghodusinejad M, Aslani A and Hachem-Vermette C (2022) Modelling community-scale renewable energy and electric vehicle management for cold-climate regions using machine learning. Energy Strategy Reviews 43:100930.

[13] Lee H, Kim K, Kim N and Cha SW (2022) Energy efficient speed planning of electric vehicles for car-following scenario using model-based reinforcement learning. Applied Energy 313:118460.

[14] Wang Y, Wu Y, Tang Y, Li Q and He H (2023) Cooperative energy management and eco-driving of plug-in hybrid electric vehicle via multi-agent reinforcement learning. Applied Energy 332: 120563.

[15] Li D, Liu P, Zhang Z, Zhang L, Deng J, Wang Z, Dorrell DG, Li W and Sauer DU (2022) Battery thermal runaway fault prognosis in electric vehicles based on abnormal heat generation and deep learning algorithms. IEEE Transactions on Power Electronics, 37(7):8513-8525.

[16] Salunkhe SS, Pal S, Agrawal A, Rai R, Mole SS and Jos BM (2022) Energy optimization for CAN bus and media controls in electric vehicles using deep learning algorithms. The Journal of Supercomputing 1-16.

[17] Ullah I, Liu K, Yamamoto T, Shafiullah M and Jama A (2022) Grey wolf optimizer-based machine learning algorithm to predict electric vehicle charging duration time. Transportation Letters 1-18.

[18] Prasanth B, Paul R, Kaliyaperumal D, Kannan R, Venkata Pavan Kumar Y, Kalyan Chakravarthi M and Venkatesan N (2023) Maximizing Regenerative Braking Energy Harnessing in Electric Vehicles Using Machine Learning Techniques. Electronics 12(5):1119.

[19] Chatterjee S and Byun YC (2023) A Synthetic Data Generation Technique for Enhancement of Prediction Accuracy of Electric Vehicles Demand. Sensors 23(2):594.

[20] Aishwarya M and Brisilla RM (2023) Design and Fault Diagnosis of Induction Motor Using ML-Based Algorithms for EV Application. IEEE Access 11:34186-34197.

[21] Kosuru VSR and Kavasseri Venkitaraman A (2023) A Smart Battery Management System for Electric Vehicles Using Deep Learning-Based Sensor Fault Detection. World Electric Vehicle Journal 14(4):101.

[22] Ullah I, Liu K, Yamamoto T, Shafiullah M and Jamal A (2023) Grey wolf optimizer-based machine learning algorithm to predict electric vehicle charging duration time. Transportation Letters 15(8):889-906.

[23] Shi L, Yang F, Gao L (2020) The Allocation of Carbon Intensity Reduction Target by 2030 among Cities in China. Energies 13:6006.

[24] Yang R. Xiong R, Ma S and Lin X, (2020) Characterization of external short circuit faults in electric vehicle Li-ion battery packs and prediction using artificial neural networks, Applied Energy 260:114253.

[25] Zhao H, Chen Z, Shu X, Shen J, Liu Y and Zhang Y (2023) Multi-step ahead voltage prediction and voltage fault diagnosis based on gated recurrent unit neural network and incremental training. Energy, 266:126496.

[26] Aishwarya M and Brisilla RM (2023) Design and Fault Diagnosis of Induction Motor Using ML-Based Algorithms for EV Application. IEEE Access 11:34186-34197.

[27] Wickramasinghe CS, Marino DL, Mavikumbure HS, Cobilean V, Pennington TD, Varghese BJ, Rieger C and Manic M (2023) Rx-ads: Interpretable anomaly detection using adversarial ml for electric vehicle can data. IEEE Transactions on Intelligent Transportation Systems.