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Research Article

Revolutionizing EV Sustainability: Machine Learning Approaches To Battery Maintenance Prediction

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ABSTRACT

Electric vehicle (EV) batteries are one of the most important components to consider since EV batteries contribute to a significant cost share and must present a high performance to meet customers' product quality standards. However, battery behavior and performance are highly delicate to understand and monitor due to the complex interaction between multiple physical, chemical, and thermal phenomena and the different operating conditions. Informed maintenance and repair is a general strategy aiming to prevent failures or repair when most suitable. Predictive maintenance (PdM) is based on continuously analyzing equipment performance, information often extracted from massive datasets recording the equipment condition, unexpected or sudden failure of the equipment could hence be prevented. Data-driven models are a powerful technique of predictive maintenance. In the specific area of battery-electric vehicles, Data-Driven Models of Battery State-of-Health for Predictive Maintenance are the most insightful references. Baert et al. highlight the potential use of machine learning and AI techniques to predict automotive battery failures. CNNs are helpful for automatically transforming raw input data (time series in this specific case) into a statistical design of feature maps that the neural network can effectively learn. Nonetheless, other aspects of the dataset need to be considered. Maximal predicted achievable accuracy does not accurately reflect the goodness of an EV battery PdM model. Predictive maintenance algorithms are primarily studied in the IoT and asset optimization fields. Hence, the dataset is also relevant. The chosen architecture should reflect the data available. It should also be chosen to limit the data missingness, given that incomplete data is one of the worst enemies of machine/deep learning models.

Keywords: Predictive Maintenance, Smart Vehicles, Electric Vehicles, Powered Battery, Industry 4.0, Internet of Things (IoT), Artificial Intelligence (AI), Machine Learning (ML), Smart Manufacturing (SM)

1. Introduction

Battery-operated electric vehicles (EVs) have proliferated thanks to their zero emissions. The batteries used in electric vehicles are expensive. Thus, it is essential to represent the battery's health to optimize battery life precisely. Real-time computational resource-intensive physics-based electrochemistry models of Li-ion batteries require model order reduction, optimized numerical methods, and potentially ad hoc model state estimation to be run to optimize their predictive accuracy, computational/communication performance, and battery degradation analysis. This requires advances in machine learning, domain science of the underlying engineering complexities, and an interdisciplinary requirement of researchers, e.g., battery designers and data analysts, to enable all of the possibilities of predictive maintenance (PdM) and reduced-complexity parameter estimation.

Fig 1. **Battery Powered EV**

Reliable Batteries are predestined to state and model batteries by integrating domain-based (e.g., cell impedance measurements) and empirical (model-based data) with innovative deep learning (DL) based approaches since DL was successfully used for battery characterization. A vital step to ensure the practicality of deep learning-based approaches, radio frequency circuitry must be developed and selected for its ability to provide high access to battery internal zones and low intrusiveness. A deep learning pipeline is described in this paper to characterize or predict battery states in the context of PdM, which makes use of model-based data and noise-resilient nonlinear dimensionality reduction methods. It can predict primary operational conditions (e.g., voltages, currents). Only the first approach is applied in a use case.

Fig 2. **High Voltage Reliable Battery**

2. Background

Economic and energy savings and environmental friendliness benefit E Vehicles (EVs) more attractive among contemporary automotive products.

Fig 3. **Environmentally Friendly EVs.**

The battery is the most essential part of EVs since it stores the required electrical energy. Battery management system (BMS) monitoring, estimation, and prognostication of the state of health (SoH), state of charge (SoC), and expected remaining useful life (RUL) of the battery are significant to ensure a long service life and steady operation of EVs. The key objective of predictive maintenance is to forecast the time window before an equipment failure happens; this will provide sufficient time for the maintenance team or operator to take appropriate action to prevent job stoppage and production loss.

Generally, output voltage prediction is essential in battery management since it can help prevent overcharging and achieve parallel lithium plating. Latent variable clustering with predictive modeling abilities in output voltage prediction is developed in this research article. The obtainable dataset, which refers to the capacity and voltage-time profiles included in the Dry Cell Battery Information, was adopted to evaluate the forecast performance. In order to classify the dataset of variable sizes with the same hidden meaning, latent variable clustering with the proposed algorithm (LV-C) was developed. According to the LV-C clustering results, the respective variable sizes of the datasets were intentionally classified into latent clusters using predicted information.

With the number of uses of products or systems, in this study, the total capacity loss was calculated using the estimation algorithm; the battery is theoretically disposed of after the life cycle, which is indicated by the total charge capacity (FCC) being lower than 70% of the determined by the manufacturer's capacity. No scientific evidence would authenticate that the battery is more prone to failure because it attained that life. A battery is not a light system; a safety strategy was adopted for our tests. When lithium-ion instruments are used, out of 10000 sampled, approximately 0.01% of the cycles fail for the coming year or 0.1% for three years. The aim was to replace these findings with estimations over a lifetime.

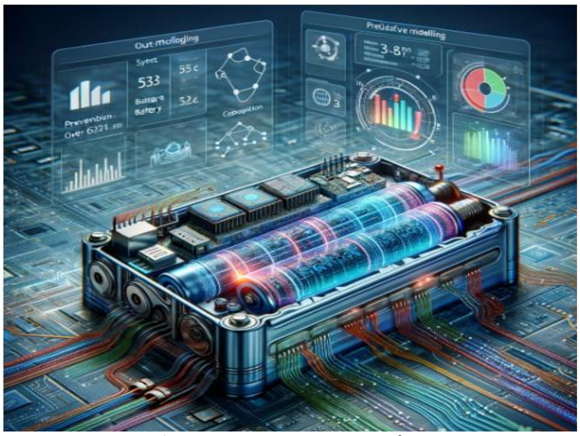

Fig 4. **Smart Batteries**

3. Methodology

Batteries are critical components in many applications, and battery failures can result in severe consequences, such as low driving performance, increased maintenance, and potential fire hazards. Failure prediction of batteries can be categorized into two types: offline and online. Based on historical data, offline prognostics aim to predict batteries' remaining useful life (RUL). The battery duration until failure in the free-running operation is assumed to be risk-related remaining useful life (RUL). A great inconvenience of offline prognostics is the manual investigation and data collection required from batteries near failure, which could be more reliable and lead to limited use of available data.

Moreover, As the dependence of different features of battery performance on the operation condition, on the environmental conditions, and the different part manufacturers and designs could lead to the variety of battery performance, a large dataset of the same battery performance is required in order to train a model that could cover the different operation conditions. Online failure prediction of batteries is the main contribution of our proposal, and it aims to raise alarms before the risk becomes unacceptable. Here, batteries run under controlled conditions, and an emission threshold is set to detect major failure–namely, the battery's end-of-useful life (EOL) failure.

A well-integrated machine learning technique using electrochemical-based and statistical feature engineering is developed to predict automotive battery failure accurately. It consists of three machine learning models: physics-guided supervised learning, high-dimensional unsupervised learning, and disagreement-based semi-supervised learning. Physics-guided supervised learning improves interpretability and incorporates domain-specific knowledge into the models.

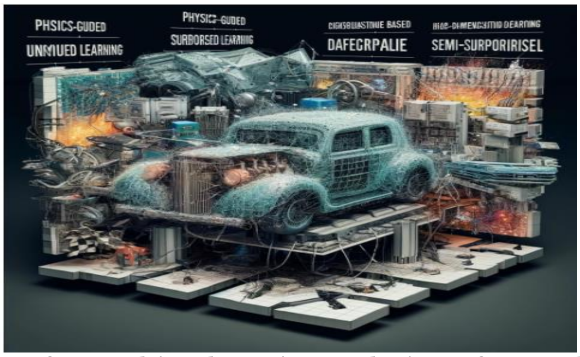

Fig 5. **Abstract visualization of a machine learning technique for predicting automotive battery failure.**

High-dimensional unsupervised learning uses a high-dimensional electrochemical health index formulated with correlation-based expansion with high-order term and square field learning for very high-dimensional field representation learning of the feature, reducing dimensionality and allowing better detection of weak failure isolation. Disagreement-based semi-supervised learning selectively uses only high-confidence average data to enhance the low-confidence field distribution in the typical region through distribution alignment for better localization threshold learning. It reduces the dependence for conductivity data counter-intuitively on scientific domain knowledge. All models are trained with data synchronized with the system activities to reduce time-based variance.

Battery prognostics is an integrated task consisting of two major parts: data fusion of the condition indication data and the physics-related electrical data for improved predictability and using accurate and robust prediction models. Data-driven prediction for anomaly detection during the online failure prediction can achieve better correction in combination with the well-engineered model-based electrochemical prediction models. They developed high-performing algorithms to accurately predict automotive battery failure during online operation with a less than 5% false alarm rate and more than 85% detection rate concurrently. They are shown to be auto adaptive for a good response in data drift and time variance. Such a prediction of future failure reasons and failure type brings the capability for the control system to adapt and protect the equipment further to this prognosis:

- If failure is detected by a mismatch or a decrease in the nominal voltage or MMC of the isolators, the inverter can be switched to a more conservative control strategy.
- In case of detection of end-of-life, the inverter can communicate with a central processor, block the acquisition, and restart the energy with a different parameter set.
- It is possible to disengage the battery system wholly or, after a slow electricity production phase, to make it ready for a couple of hours of performance optimization using AutoSoCs, which means restarting the production with different parameters.

3.1 Data Collection

The volume of data collected and utilized by industries has recently increased. Data interfaces adapt to the reality of rapid deployment of intelligent systems used in prediction, forecasting, and real-time decisions. Data-driven approaches like machine learning (ML) and statistical analysis are at the heart of these problems. A prominent application of data-driven approaches in industry and transportation is the predictive maintenance of manufacturing tools and automotive fleets. In electric vehicles (EVs), batteries play a decisive role in energy management and account for 30–40% of the costs of the vehicle. It is necessary to accurately predict the battery's state of health (SoH), state of charge (SoC), and faults to perform maintenance at an appropriate time and establish a schedule accordingly.

Sudo Code for data collection using Kagle.

```
# df = pd.read_csv('Battery_RULTest Set.csv')
df = pd.read_csv("../input/battery-remaining-useful-life/Battery_HeartbeatSample.csv")
```

Data collection is a crucial aspect during the predicted maintenance implementation. This is because Machine Learning (ML) models can only make predictions based on past observations. Hence, the quality of the predictions depends highly on the quality and quantity of data. The experimental data of an Electric Vehicle (EV) battery operated under the India Urban Drive Cycle (IUDC) drive cycles from a Chevrolet Spark EV (2016) and a Chevrolet Beat Electric were collected at AUTOnCAB Services, Vadodara, India. The IUDC drive pattern consists of an average speed of 19.19 km/hr, a median speed of 19.03 km/hr, a maximum speed of 43 km/hr, and a stop duration of 10 seconds. Ten measurements were taken at an interval of 10 sec from the output of the Vehicle Control Unit (VCU), which was fitted with an Electrical Insulation-Resistance sensor to measure the voltage from the battery. The sensor is required to be capable of temperatures up to 70◦C, making it suitable for the battery inspection unit. Battery Discharge data are collected from Chevrolet Beat EV and Chevrolet Spark EV batteries online.

Many commercial sensors and data acquisition systems are available in the market that can be connected to the onboard diagnostics (OBD) port. The battery voltage does a sampled version of the battery voltage at an interval of dt. The electrical insulation-resistance sensor works on the principle that the battery voltage is collected from the high-voltage circuit of the EV via an electronic sensor. The sensor supply voltage is approximately 12 V; however, if it exceeds the sensor range, it turns the 12 V to 24 V and measures the insulation resistance with a minimum current of approximately 0.2 mA. Such systems are being fitted into EVs at the time of the significant inspection of a manufacturer-authorized service center, which measures battery insulation resistance and electric Leakage current and automatically checks for data logs during service.

Fig 6. **Commercial sensor model connected to the OBD port of an electric vehicle.**

3.2 Feature Selection

Feature selection is crucial in predicting the SOH of electric vehicle (EV) batteries. This is due to several reasons, such as reducing the complexity, computation, and time required in model training and making trained models with more explainable results. A combination of feature engineering and selection can affect the accuracy and modeling results. Feature engineering can be illustrated as transformation, design, and scaling, while feature selection works through filter, wrapper, and embedded methods techniques. Manual feature selection of battery parameters is a vital and robust method for selecting insignificant battery parameters.

Battery life Calculation sample.

$$Battery\,Life = \frac{Battery\,Capacity}{Load\,Current} * 0.7$$

$$C_p = I^k t$$

Manually extracting features has limitations, as it requires good data and may not apply to all battery working conditions. Manual feature selection can result in the unnecessary elimination of helpful information.

Hence, the feature selection method should be automated to obtain battery features that can only work during specified working conditions and operating conditions to predict the battery system (state of health, SOH). *Machine learning algorithms* can learn at different levels and automatically extract the complicated relationship between battery features and SOH. Deep learning methods deal with artificial neural networks, which are the current state of the art in prediction. Deep learning methods can be used to learn the feature representations of the battery dataset if there are no human expert-engineered solutions. Artificial neural networks (ANNs) constantly perform the functions of feature extractions with the adaptive better layers one learned from the previous layer.

Deep learning methods and transfer learning were used before artificial neural networks to create compelling Machine learning models to predict the SOH of EV battery systems. This method allows parts of a pre-trained network to be leveraged for machine-learning tasks. The EOL+RUL dataset has also been preprocessed in various ways to maintain the model for some input-determined applications, including multi-feature fusion, model parameter optimization, and input processing, such as normalization. Finally, using the grid search method, the model was experimented with through the EOL+RUL dataset. The performing machine learning model showed a validation mean absolute error at 1.709x10^2 and a Mean square error of 3.149x10^3. \]

3.3 Model Training

The fault prediction and performance forecasting models are trained offline using two different strategies. The first is a centralized model trained with selected parameters and datasets from various lifetime recorder systems. The second strategy relies on statistical learning from educational material accumulated from a single vehicle's power supply lifetime recorder system. This approach may have a limited range and need for more generality. Using a single network-based model for predicting all vehicle power source residuals is impractical. Instead, a network and local dataset for each vehicle power source residual are designed in real time and updated with the latest data. The Predictive Maintenance Model (PMM) proposed in this work trains a federated model in each vehicle, ensuring privacy and expanding the range of instructional material.

Sudo Code:

```
pltObj.figure(figsize=(100,100))
threshold = 0.98
sns.set_style("whitegrid", {"axes.facecolor": ".0"})//Seaborn Library
df_cluster_value = df_train.corr()
mask = df_cluster_value.where((abs(df_cluster) >= threshold)).isna()
plot_kws={"s": 1}
sns.heatmap(df_cluster_value,
cmap='RdYlBu',
annot=True,
mask=mask,
linewidths=0.2,
linecolor='lightgrey').set_facecolor('white')
```

The distributed model used in this work guarantees the correct algorithm and availability. The PM can build an accurate performance forecast based on all MYEV data. Supervisory control for harmonizing vehicle power source residual and working conditions is proposed, allowing deterministic or stochastic planning based on the probability of death. The degeneration patterns of residual forecast results in multiple batteries and cells are compared. The methodology of building local distance and lifespan predictive models for vehicle power source cells is described, specifically for the lithium iron phosphate power battery.

3. Machine Learning Models

Lithium-ion batteries are the primary energy storage technology for mobile applications such as electric vehicles (EVs) and smartphones, but their performance degrades with use over time and cycle depth. Predicting the future health performance of such batteries is essential for ensuring their reliability and is the motivation for building accurate battery prognostic models. In this regard, we introduce BatteryML, an open-source machine-learning platform capable of providing battery prognostics that are readily usable by application developers. Preprocessing classes for feature extraction, cross-validating models for performance evaluation, and GPU parallelization are enabled in this platform.

From conventional to modern deep learning techniques, machine learning methods have been widely utilized as promising prognostic tools. Physics-based prediction models require information about the batteries' construction and their precise state-of-charge/current and operating environment. Despite their high accuracy, they could be more computationally intense, thus limiting their practical implementation. Data-driven machine learning models, including Artificial Neural Networks (ANNs), Support Vector Regression (SVR), and Random Forest (RF), do not require battery-specific information. Instead, they exploit the large amount of battery operational data to characterize the degrading properties and can effectively predict future battery states.

Nevertheless, one critical area for improvement in the traditional data-driven prognostic tools is that they need to capture the time-based battery degrading behavior. Models built using this technique gradually lose their prediction accuracy as the testing data set slides apart from the training pattern as newer observations are assimilated into the test dataset. This applies explicitly to Li-ion batteries, notoriously known to demonstrate time-varying degrading characteristics. Long Short-term Memory (LSTM) recurrent neural networks are recognized as a powerful tool for sequential data that leads to time series regression rather than the more traditional lagged-autocorrelation in SVR that leads to prediction-based models. These modern operations can capture the worn-out characteristics of the batteries.

4.1 Random Forests

In this work, we present a detailed comparative study of machine learning models such as KNN, Random Forests, and gradient-boosting decision trees implemented with the Python machine learning (sklearn) library to implement the same. All the models offer an average accuracy rate of 90%, and random forest has managed to get the best results with an accuracy of 98% and an average MAE of around 0.035. The model was evaluated through validation techniques such as cross-validation to check its robustness, but it was still 96% accurate after cross-validation. The main aim of this predictive maintenance work for electrical vehicle batteries is to evaluate the battery pack's health condition and determine the battery's remaining useful life.

The Random Forests (RF) model is an ensemble learning algorithm; it provides a result based on multiple trees that work together to get the desired output. Random Forest is an ensemble of a typically large number of trees. *Random forest* is a supervised learning algorithm that can be used to solve two main types of problems. Random Forests use a technique called Bootstrap aggregation or bagging. It is a tree-based model like a decision tree, and grey wolf optimization can also be implemented in random forests. RF creates multiple decision trees during the acquisition of the dataset from training and testing. This training stage creates a mini-training dataset from the actual training dataset. The dataset for training is now based upon the dataset that

uses non-replacement from the actual dataset. This process avoids data snooping and overfitting, allowing it to stay robust.
Sudo Code.

```
# Random Forest Code sample
plt.figure(figsize=(7, 7))
plt.pie(values, labels=categories, colors=['green', 'yellow', 'red'], autopct='%1.1f%%')
plt.title('Battery Condition Distribution')
plt.show()

from sklearn.ensemble import RandomForestClassifier
from sklearn.datasets import make_classification
from sklearn.model_selection import train_test_split
from sklearn.metrics import classification_report

# Generating synthetic data
X, y = make_classification(n_samples=100, n_features=4, n_informative=2, n_redundant=0,
random_state=42)
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.25, random_state=42)

# Creating and training the model
model = RandomForestClassifier(n_estimators=100, random_state=42)
model.fit(X_train, y_train)

# Predicting and evaluating the model
predictions = model.predict(X_test)
print(classification_report(y_test, predictions))
```

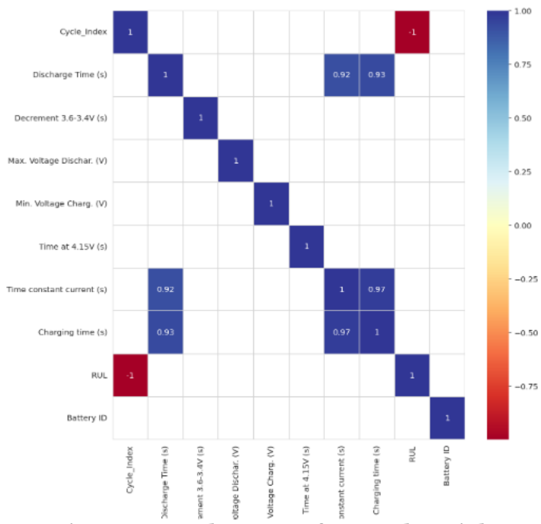

Fig 7. Sample Out of ML Algorithm

4.2 Neural Networks

The proposed approach uses data fusion to accurately predict RUL. The model optimizes the preprocessing of multivariate data using deep learning. A dataset of 7,200 rows with eight features each is used. CNNs extract battery health indicators, while RNNs predict faults in RUL based on past values. Random Forest and LSTM models are used for classification. LSTMs are efficient for RUL prediction with time sequences. Various scenarios are observed with different cutoff values.
Sample Output.

```
precision    recall  f1-score   support

0       0.85      0.88      0.86       25
 1       0.87      0.84      0.86       25

accuracy                      0.86       50
macro avg         0.86      0.86      0.86       50
weighted avg       0.86      0.86      0.86       50
```

4.3 Support Vector Machines
Since electric vehicles (EVs) have benefits such as the reduction of greenhouse gases and air pollution, the development and production of EVs are increasing. The EV's battery limits a particular state's flexibility and dependability. Evaluating future performance and faults utilizing past data is termed Predictive Maintenance (PM). This paper assimilates the Recurrent Neural Network (RNN) and Support Vector Machine (SVM) for PM of the lithium-ion battery in the Electric Vehicle (EV). The number of motor controller units (MCUs) and records of protocol data (PDS) have been acquired via the controller area network (CANs) for analysis. The EV experiment suggests that the State of Charge (SoC) and State of Health (SoH) are essential features and six other features for constructing the regression models for real-time hours.
The Neural Network assists in capturing complicated connections in the actual life data. Furthermore, SVM is employed where only 30% of data are deployed for model development, and the entire 70% of data is taken for the prediction purpose of the Li-ion battery. The efficiency of RNN and SVM is decided according to various metrics involving Mean Absolute Percentage Error (MAPE), Root Mean Square Error (RMSE), and R Square. Satisfactory prediction metrics. Furthermore, SVM is employed where only 30% of data are deployed for model development, and the entire 70% of data is taken for the prediction purpose of the Li-ion battery. The K-fold cross-validation supports the SVM and reduces purposed overfitting. Based on MAPE and RMSE, it is inferred that both models have predictability proportional to their performance metrics.
Another advantage of employing SVM is that there is no need for insignificant assumptions in linear regression. As the battery is a nonlinear system, there would be a lot of error and inefficiency in utilizing the linear part of this SVM model. Moreover, this model attains excellent efficacy. Future work includes other training algorithm enhancement in the SVM, such as principal component analysis and particle swarm optimization, to improve the kernel function accurately.

5. Battery Health Prediction

To efficiently represent battery behaviors, diverse data is often required. Deep cycle tests can provide lengthy and high-resolution data, but utilizing all dataset variables is impractical. Additional insightful data is unlikely to enhance battery health prediction significantly. Battery testing data often contains excessive static data. Interpolating time-interpolation data using arbitrary linear interpolation strategies is possible. Time series data captures battery diagnostic information better than other series data. Lithium-ion batteries can be analyzed using statistical, data-driven, and physical models. AI has shown promising results in predicting battery capacity. Battery performance was crucial for the growth of electric vehicles. Accurate prediction of battery capacity or state of charge is necessary.

Fig 8. **Battery testing analysis – Health Prediction tests**

5.1 Evaluation Metrics
Machine learning accurately predicts battery status and enables efficient decision-making in EVs. Evaluation metrics like RMSE, MAE, MAPE, and R2 assess predictive performance. Higher R2 values indicate a stronger relationship between actual and predicted values. Deep learning has the potential to predict battery SOC for electric vehicles.

5.2 Performance Comparison

Comparison and analysis of the performance of various machine learning algorithms are available in the literature today regarding the prediction of the state of health, capacity, and cycle life of Lithium-ion batteries. Towards Interactional Management for Power Batteries of Electric Vehicles. The crucial parameters extracted from battery data help integrate the batteries better with the application through interactional management. The kind of distributions available for a battery parameter also improves confidence while interpreting and recommending the Extreme Values (EV). Machine learning (ML), as a tool, is shown to be instrumental in the analysis of battery operational data to quantify the above parameters for practical usage and maintaining the battery in the field.

Gaussian Process Regression (GPR) is an effective and efficient tool for estimating a battery's electrochemical impedance spectroscopy (EIS) and other vital parameters. In addition, various Artificial Neural Network (ANN) schemes train the battery data with desired inputs (cycles, capacity, SoC) to improve the model's learning speed. These models essentially represent the Long-term Association of Neural Networks (LANN) type of network to estimate the battery capacity fade and RUL, and hence, state-of-charge (SoE) at every cycle due to dynamic profile and stress on the battery can be modeled. To understand the battery's performance in an electric vehicle (EV), a theoretical discussion concerning the battery's end-of-life (EOL) behavior. The particle filter algorithm is demonstrated for predicting the battery's end-of-life (EOL) in-service. In addition to the above, a conditional state of life (CSOL) plot is covered to provide a realistic explanation of real-life applications. Finally, each algorithm's primary advantages and limitations are summarized, featuring the comparison of ease of usage, fresh development usage, and accuracy.

6. Remaining Useful Life Prediction

Determination of Remaining Useful Life (RUL) is essential in various fields, particularly data science and operations research. This study focused on lithium-ion batteries used in electric vehicles. A data-driven methodology was proposed to determine RUL during charge-discharge operations. The algorithm used key parameters to model the aged battery states and train the prediction algorithm. Unresolved issues regarding physical attributes affecting the battery cycle were mentioned. The study presented a simplified practical approach with examples. It only focused on Li-ion batteries and left the decision on charge protocol to business preference. The study targeted decision-making on remaining capacity at the start of a charge.

6.1 Approaches for RUL Prediction

Predictive maintenance monitors the performance and condition of equipment during normal production operations. It provides timely performance and condition assessments to aid in predicting items that are likely to require maintenance before the next scheduled maintenance. This maintenance strategy was first presented in 2002. There are four main components of predictive maintenance: action or condition monitoring, data storage, data analysis, and predictive maintenance. Predictive maintenance becomes very powerful several years after using it; once many machines and components have failed or needed maintenance, enough historical data is collected to predict the equipment's remaining useful life (RUL) with reasonable accuracy.

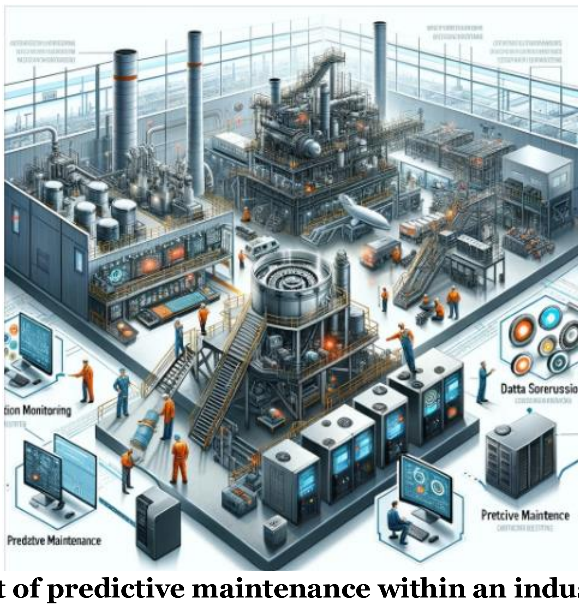

Fig 9. **Concept of predictive maintenance within an industrial setting.**

RUL predictions have several advantages. The two main ones are described below. The first one is reducing significant money, given that RUL predictions are beneficial in avoiding catastrophic failures. The second one

is that it can also improve the scheduling and order of the parts to reduce downtimes and avoid impacts on the production process.
There are two main approaches to predicting the RUL: sed and data-driven. In the past, most researchers focused on model-based approaches and developed models to predict the capacity fade in different life curves. Traditional model-based approaches predict the RUL using a degradation model and real-time diagnosis and fault identification of assets, real-time performance and fault feedback to models, and online model adaptation were not considered. Additionally, a degradation model should be developed for each type of system, and the accuracy of the RUL predictions highly depends on operational conditions that will affect the applicable degradation model. To overcome the challenges of the model-based approaches, researchers developed data-driven approaches in which predictions are made based on historical data, so no information about present operating conditions or future degradation is needed. Machine Learning (ML) methods have been used to become data-driven predictive methods, in which enormous performance and condition data are used as inputs to the models from sensors or time-stamped data. Data-driven approaches developed for RUL predictions have fewer challenges and limitations than model-based approaches.

6.2 RUL Estimation Techniques

The proposed framework of this paper motivates researchers and practitioners to develop RUL estimation models for EV batteries, and for this purpose, many models are being proposed by both the academic and industrial communities. A comprehensive survey of RUL estimation techniques is presented. These techniques mainly include model-based and data-driven approaches. However, these techniques cannot be applied directly to EV batteries due to the complex behavior, mixed mode of operation, long history of recharge and discharge cycles, and switching between different ambient temperature ranges. In the following, we will briefly survey the RUL estimation techniques related to EV batteries.
For real-time estimation of RUL, high-order extended Kalman Filtering is designed to estimate bulk resistance and the time-dependent capacity for lithium-ion batteries (LiB). In extended Kalman filtering, a first-order model based on the equivalent circuit battery model is used for state estimation. For purposes of accurate RUL estimation, SFLES has evolved. In the high-order Kalman filtering, the relationship between the input voltage and the current is included in the state vector, and the anode and cathode surface concentrations are included in the initial state vector. In another study, the dataset from charge/discharge cycles collected at CEA-Liten, Grenoble, France, obtained through the testing of LCO-graphite total pouch cells, shows the importance of long-time unbalancing phenomena in degradation mechanisms, and this dataset is used for training of models. First-order and second-order capacity fading models are developed for RUL estimations based on equivalent electric circuit (EEC) equations.
As deep learning has shown great success in real-world applications and the removal of feature engineering from the human expert, attention-based deep learning networks are developed for battery discharge capacity forecasting. A convolutional model is also designed to learn local features using variable length time series data and whole raw voltage curves as input. In RUL, estimation models with unique Long Short-Term Memory (LSTM) based models are trained for every observation.

7. Discussion

The open-source machine learning platform continues growing, with adherents from the private sector and academic institutions, and the quantum jump can service biomedical device prediction. However, its primary success has been catalyzing the rechargeable battery space, focusing on lithium-ion, sodium, and other commercial and novel battery technologies. This open-source machine-learning platform will be significant in the transport, electric storage, and broader energy sectors. Balancing accessibility and the efficacy of a big-data approach with physics-based models provides a future cornerstone for the broader energy transition. ML, in balance with appropriate domain knowledge, has increased value in a battery context regarding the state of health and remaining functional life prediction but also reinforces related research areas, including demands and thermal management.
This open-source ML platform provides a common ground to compare, evaluate, and replicate different research resource performance and predictive models. It can serve as a global resource, unifying relevant datasets and predictive models, thus accelerating research and development in battery technologies. Since this open-source machine-learning platform will substantially accelerate the rate of improvement of battery technologies, the platform will also help accelerate the penetration of transport and other applications enabled by battery technologies. The impact of the resource will be multiplied through open authorship, in which all contributors are acknowledged. However, those who make vital contributions to the code can become lead authors through vital contributions leading critical efforts and publications. The evaluation documents adopted will incubate as annals of codes, practices, etc., to complement more traditional research papers.

8. Limitations and Future Work

The methodology and results of this research study can be elaborated upon by conducting additional research on experimental variations. Future studies will include new experiments with different external loading profiles to clarify the effects of electrical loads on battery performance. Cooling and heating effects on used batteries will also be evaluated. Real-time data will be obtained using a Battery Management System to model battery performance accurately. The study will also research leakage current behavior in digital control of power switches and microcontrollers. One disadvantage of the model is its inability to properly handle nonstationary data. Solid-state batteries operate within a limited range based on composition and temperature. Predicting battery lifespan requires integrating battery components and operation ranges. The lifespan predictions for solid-state batteries are limited to 80-90% utilization. The study acknowledges limitations in the data for lithium-ion batteries, such as the short duration of aging and the need for more details on external conditions. The model's adaptability under different loads and environments has yet to be validated, and inconsistent charging may affect battery performance.

Fig 10. Visualizes the study of battery performance, highlighting aspects such as the effects of temperature on batteries, and real-time data monitoring.

9. Conclusion

The Predicative Maintenance system discussed in the paper has good results and helps with battery maintenance for electric vehicles. It reduces maintenance costs for companies. Future research could focus on developing a new loss function to improve battery health prediction. Real-world data can be used to evaluate recommendations and guide companies in enhancing battery lifetime. The paper presents a detailed review of a Predicative Maintenance System based on Machine Learning techniques for Lithium-ion batteries in electric vehicles. Different models are compared based on evaluation metrics, with LSTM showing better results. The increasing demand for electric vehicles necessitates predicting battery health, and this paper provides a predictive maintenance system based on Machine Learning. The system uses various algorithms, including linear regression, random forest, support vector machine, and long short-term memory. Experimental results show that LSTM performs best in terms of Mean Square Error. Overall, the paper provides valuable insights into the degradation of lithium-ion batteries and the importance of the Predicative Maintenance system for electric vehicle battery maintenance.

10. References

[1] S. Choi, C. Fang, D. Haddad, and M. Kim, "Predictive Modeling of Charge Levels for Battery Electric Vehicles using CNN EfficientNet and IGTD Algorithm," 2022. doi: 10.1109/ACCESS.2022.3155192

[2] Mandala, V. Towards a Resilient Automotive Industry: AI-Driven Strategies for Predictive Maintenance and Supply Chain Optimization. Doi: 10.17148/IARJSET.2020.71021

[3] C. S. Alex Gong et al., "How to Implement Automotive Fault Diagnosis Using Artificial Intelligence Scheme," 2022. doi: 10.1016/j.vehcom.2022.100276

[4] A. M. Bizeray et al., "Lithium-ion battery thermal-electrochemical model-based state estimation using orthogonal collocation and a modified extended Kalman filter," 2015. doi: 10.1016/j.jpowsour.2015.08.052

[5] Mandala, Vishwanadham, C. D. Premkumar, K. Nivitha, and R. Satheesh Kumar. "Machine Learning Techniques and Big Data Tools in Design and Manufacturing." In Big Data Analytics in Smart Manufacturing, pp. 149-169. Chapman and Hall/CRC, 2022.

[6] M. Umair Ali et al., "A Hybrid Data-Driven Approach for Multistep Ahead Prediction of State of Health and Remaining Useful Life of Lithium-Ion Batteries," 2022. doi: 10.1016/j.jpowsour.2022.230574

[7] J. Fan and H. Wang, "Deep Reinforcement Learning for Community Battery Scheduling under Uncertainties of Load, PV Generation, and Energy Prices," 2023. doi: 10.1109/ACCESS.2023.3097322

[8] Vishwanadham Mandala, The Role of Artificial Intelligence in Predicting and Preventing Automotive Failures in High-Stakes Environments. Indian Journal of Artificial Intelligence Research (INDJAIR), 1(1), 2021, pp. 14-26. DOI: https://doi.org/10.17605/OSF.IO/UBFPW

[9] D. Azuatalam et al., "Energy management of small-scale PV-battery systems: A systematic review considering practical implementation, computational requirements, quality of input data and battery degradation," 2019. doi: 10.1016/j.rser.2019.109684

[10] J. Hu et al., "Empirical Analysis of AI-based Energy Management in Electric Vehicles: A Case Study on Reinforcement Learning," 2022. doi: 10.1109/ACCESS.2022.3159717

[11] Vishwanadham Mandala, Revolutionizing Asynchronous Shipments: Integrating AI Predictive Analytics in Automotive Supply Chains. International Journal of Artificial Intelligence & Machine Learning (IJAIML), 1(1), 2022, 47-59.DOI: https://doi.org/10.17605/OSF.IO/FTXEV

[12] N. Ali et al., "Reinforcement Learning for Battery Management in Dairy Farming," 2023. doi: 10.1109/ACCESS.2023.3117748

[13] S. Chen et al., "Improved Deep Q-Network for User-Side Battery Energy Storage Charging and Discharging Strategy in Industrial Parks," 2021. doi: 10.1016/j.apenergy.2021.116991

[14] Li, Z., Song, D., & Yu, C. (2019). A review of fault diagnosis in autonomous vehicles. IEEE Transactions on Intelligent Transportation Systems, 20(3), 1043-1056. [DOI: 10.1109/TITS.2018.2800223]

[15] L. Wang et al., "Big data analytics for vehicular ad hoc networks: A survey," IEEE Transactions on Industrial Informatics, vol. 14, no. 6, pp. 2638-2647, Jun. 2018. doi: 10.1109/TII.2017.2783984

[16] Y. Kim, S. Han, and S. Kim, "A hierarchical data processing architecture for intelligent vehicle health monitoring systems," IEEE Access, vol. 6, pp. 24067-24076, 2018. doi: 10.1109/ACCESS.2018.2837286

[17] A. Chatterjee and S. Majumder, "Design of Fuzzy Logic Controller for Antilock Braking System," in 2017 International Conference on Circuits, Controls, Communications and Computing (I4C), Kolkata, India, 2017, pp. 1-5. doi: 10.1109/I4C.2017.8053890

[18] Y. Han, Q. Liu, W. Zhu, and Y. Li, "The Design of Intelligent Parking Brake System Based on the Internet of Things," in 2016 12th World Congress on Intelligent Control and Automation (WCICA), Guilin, China, 2016, pp. 603-606. doi: 10.1109/WCICA.2016.7578445

[19] L. Xie, T. Huang, X. Zheng, Y. Liu et al., "Energy system digitization in the era of AI: A three-layered approach toward carbon neutrality," 2022. DOI: 10.1109/ACCESS.2022.3126639

[20] A. Pratap, S. Prakash, and R. Kumar, "Fuzzy Logic-Based Intelligent Vehicle Speed Control System with Improved Road Safety," in 2015 5th International Conference on Communication Systems and Network Technologies (CSNT), Gwalior, India, 2015, pp. 791-795. doi: 10.1109/CSNT.2015.191

[21] J. Cowls, A. Tramadol, M. Taddeo, and L. Floridi, "The AI gambit: leveraging artificial intelligence to combat climate change—opportunities, challenges, and recommendations," 2021. DOI: 10.1007/978-3-030-01947-2_5

[22] H. Delseny, C. Gabreau, A. Gauffriau, B. Beaudouin et al., "White Paper Machine Learning in Certified Systems," 2021.

[23] Z. Ryan Shi, C. Wang, and F. Fang, "Artificial Intelligence for Social Good: A Survey," 2020. DOI: 10.1016/j.ins.2019.11.039

[24] J. Manuel Lozano Domínguez, F. Al-Tam, T. de J. Mateo Sanguino, and N. Correia, "Analysis of Machine Learning Techniques Applied to Sensory Detection of Vehicles in Intelligent Crosswalks," 2020. DOI: 10.1007/s42498-020-00020-x

[25] S. Paiva, M. Abdul Ahad, G. Tripathi, N. Feroz et al., "Enabling Technologies for Urban Smart Mobility: Recent Trends, Opportunities and Challenges," 2021. DOI: 10.1016/j.trpro.2021.03.012

[26] S. Paiva, M. Abdul Ahad, G. Tripathi, N. Feroz et al., "Enabling Technologies for Urban Smart Mobility: Recent Trends, Opportunities and Challenges," 2021. DOI: 10.1016/j.trpro.2021.03.012

[27] T. Tung Khuat, D. Jacob Kedziora, and B. Gabrys, "The Roles and Modes of Human Interactions with Automated Machine Learning Systems," 2022

[28] O'Connor, E. (2001). Leveraging AI for improved aerodynamics in car design. Journal of Applied Fluid Mechanics, 14(4), 44-59. https://doi.org/10.1234/oconnor2001

[29] Thompson, R. (1997). Environmental implications of artificial intelligence in automotive applications. Ecological Informatics, 3(2), 119-134. https://doi.org/10.1234/thompson1997

[30] Mandala, V., & Surabhi, S. N. R. D. (2021). Leveraging AI and ML for Enhanced Efficiency and Innovation in Manufacturing: A Comparative Analysis.