A Review on Performance Prediction Models for Battery Life in IoT Networks

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***Abstract*—The Internet-of-Things (IoT) has revolutionized virtually every sector, providing new and improved solutions through connectivity. Nevertheless, the prudent monitoring of power in the case of IoT gadgets continues to be an obstacle. This paper explains the importance of forecasting the early death of batteries to optimise the life and performance of an IoT network. In addition, this paper extensively reviews the data-driven models to predict the lifetime of battery especially, neural-nets approach - machine learning (ML) models. This paper analyzes the wide range of ML models applied in the remote sensing domain and provides an extensive evaluation of their strengths and weaknesses regarding their performance. Furthermore, the paper provides interesting recommendations to mitigate the identified limitations in these methods to improve the accuracy of the battery lifetime predictions. This review aims to guide future research efforts towards the development of robust and effective strategies for battery life conservation in IoT networks.**

***Index Terms*— Performance Prediction Models, Battery Life and IoT Networks**

I. INTRODUCTION

THE current time is in favor of technology implementation for the discovery of real-world problems. There is a lot about technology that is routinely expressed in daily activities. Nowadays the IoT is a widely used networking technology [1], [2]. Real-time collection from everyday objects The IoT is transforming the way data is collected - for the first time, giving access to data in real-time. The data can be processed to extract valuable insights that can be leveraged to lead to greater operational efficiency and informed decision-making across a plethora of industries [3]. Inclusionally, the IoT consists of networked sensors on the internet that are designed information to the IoT device [4]. IoT advances alongside to be controlled over the internet and indirectly give smart tech and communication strategies have exaggerated the adoption of energy-saving networks [5],[6]. The applications in the real world of IoT technology have a lot of challenges, one of the main challenges among them is battery life in devices that are used over IoT networks [7]. IoT devices draw different amounts of power, depending on what you use them for during sleep mode, the sensors are designed to operate at less energy, and during active mode towards sending bulk data, sensors are assigned more energy to be executed. Energy consumption in IoT applications increases according to the used components, so the calculation of the battery life is very important [8],[9].

Decision-making can be based on performance, self-discharge, and safety when having to decide between rechargeable and disposable batteries. Disposable batteries are cheaper but produce more waste and deteriorate quickly in performance thus not recommended for high-power devices, you need to go for rechargeable batteries. For the batteries deployed in large numbers in IoT applications, this monitoring is essential to keep up the life of the battery. Though it revolutionizes the way of living across the globe, and yet IoT integration encountered power management, security, and wireless communication, but few limitations flag constant energy monitoring and prediction [10]. The research paper highlights the essentiality of early prediction of battery life in relation to the enhancement of network lifetime and network performance (in IoT). Its management approach adopted a data-driven model in ML, what their strengths and weaknesses are, and how data-driven models must be chosen appropriately. Additionally, it offers recommendations to improve the accuracy of these predictions.

The organization of the rest of the paper is as follows: the literature review is discussed in Section II, the methodology is discussed in Section III, performance prediction models are discussed in Section IV, the significance of battery life in IoT networks is detailed in Section V, the estimation of battery life using performance prediction models is explored in Section VI, the discussion of the models and their implications is provided in Section VII, and the conclusions and future directions are outlined in Section VIII .

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II. LITERATURE REVIEW

When it comes to this kind of diversity, however, battery life prediction remains a particularly difficult issue. Several research works have thus sought to develop models that can predict the lifespan of batteries used in these gadgets to enhance timely recharging or replacement. Patil and Kendule (2024) conducted a study that addressed the problem of Lithium-ion battery downgrading in electric vehicles using an IoT setup for monitoring them on the ThingSpeak cloud platform. They did this by creating an Artificial Neural Network (ANN) model with National Aeronautics and Space Administration (NASA)'s battery dataset which predicts the Remaining Useful Life (RUL) of batteries revealing capacity degradation over cycles. High accuracy is demonstrated by the ANN model's prediction of battery RUL before its End-of-Life (EoL) [10]. Macias and Trilles (2024), on the other hand, have used ML to predict when the IoT device's battery will run out based on two things: the charge level and the weather. It was quite accurate, reaching 94.09%, which made energy management in IoT networks that use renewable energy better. As a result, this study has significant implications for improving the energy management of reliable solar-powered devices [3].

However, the requirement for a proficient battery the executives isn't simply restricted to this planet; it takes us further away into space. However, Shibl et al. (2023) have presented an AI-based Battery Management System (BMS) for Unmanned Aerial Vehicles (UAVs) that spotlights on State-of-Charge (SoC) and State-of-Health (SoH) expectations. In completing this, deep neural networks (DNNs) and Long Short-Term Memory (LSTM) networks were utilized to accomplish high exactness in SoC and SoH assessments through genuine robot execution. The classification accuracy of the Random Forest (RF) model was 92% [11]. Batta et al. (2023), on their part, made an introduction of Lifetime Extension Clustering Algorithm for State of Health (LECA_SoH) as a clustering approach in IoT network optimization aimed at extending the life of IoT networks by predicting battery SoH. Based on data from NASA's Prognostic Data Repository, it predicts cluster head election influence on battery SoH thereby increasing network lifespan. This research indicates that LECA_SoH improves life span and recharge cycles compared to traditional energy-efficient approaches [12].

Siva et al. (2022) discussed the battery life prediction challenge of IoT applications running on renewable energy sources, concentrating on battery prediction problems and joint access control in an IoT cell system. This study proposes a hybrid algorithm that employs LSTM and Principal Component Analysis (PCA) to predict battery life in IoT networks. Applying a hybrid Q network (HQN) with LSTM can solve the problem of access control and can increase the precision of the battery prediction (by up to 92%) compared to traditional algorithms such as k-nearest neighbors (kNN), RF, and support vector machine (SVM). It has been validated on the Individual household electric power consumption (IHEPC) dataset and this approach showed promising results [13]. Gandhi et al. (2022) designed a BMS with IoT and ML to estimate the SoC and SoH) of batteries utilizing IoT sensor data, the study predicts with high accuracy enhance battery efficiency and lifespan. Although the results are promising, the limitations include the requirement of different datasets and varying environmental conditions for evaluations [14].

In the predictive modeling field, Bhattacharya et al. (2021) introduced a DNN framework with memory features (DNNwMF) to predict the RUL of lithium-ion batteries using NASA and University of Maryland datasets. The method based on autoencoder and DNN increased the accuracy of RUL prediction capability by reducing about half of the root mean square error (RMSE) compared with models without memory features. This study portrays a crossroads where the complexity of the model meets the efficiency of the model, implying a trade-off relation to the size of the optimization space and the prediction accuracy yield [5].

The study by Reddy Maddikunta et al. (2020) developed a predictive model using a dataset from 'Beach Water Quality – Automated Sensors' in Chicago, employing a RF regression algorithm. The model was 97% accurate in predicting the need for battery replacement and hence helps in continuous IoT services Integration of discharge time and charging time with the battery's SoH in the existing study showed significant association and the RF algorithm was superior in comparison to other algorithms by 12% difference in accuracy [8].

Ren et al. (2020) develop a data-driven RUL prediction model for lithium-ion batteries, combining convolutional neural network (CNN) and LSTM networks. Their auto-CNN-LSTM architecture captures temporal degradation patterns effectively. The model generalizes well across datasets, demonstrating robust predictive capabilities. Results show a promising mean absolute percentage error (MAPE) of 5.342%, suitable for practical applications [15]. The study by Somayaji et al. (2020) has contributed to the creation of a blockchain-tailored framework to predict the prognosis of battery life on the IoT using DNNs. The use case explored in the study is the beach from the Chicago Park District, which collects data in real-time from several sensors.

The process here includes training of DNN model on the dataset to predict the battery life which then stores these predictions in a blockchain through decentralized and secure storage. The new framework results of the study demonstrated high accuracy in predicting the battery lifetime [1].

A summary of all the literature on prediction models to evaluate battery life in IoT networks has been provided in Table I. This table includes references, objectives, datasets, methodology, results, and limitations.

TABLE I
SUMMARY OF ALL THE LITERATURE ON PREDICTION MODELS TO EVALUATE BATTERY LIFE IN IOT NETWORKS.

Ref	Year	Objective	Dataset	Methodology	Results	Limitations
[10]	2024	Address challenges of battery downgrading and potential hazards in EVs	NASA's battery dataset for discharge cycles	IoT setup to monitor battery condition; ANN model for RUL prediction	High accuracy in predicting RUL before reaching EoL	Limited to the dataset used, may not generalize to all battery types
[3]	2024	Predict battery levels in IoT devices using ML and meteorological data	Battery charge data and weather forecast records	ML models to analyze and predict battery charge levels	High predictive accuracy, with up to 94.09% accuracy in test scenarios	Dependent on accuracy of weather forecasts and limited dataset
[11]	2023	Develop a BMS for UAVs focusing on SoC prediction and SoH estimation	Battery charge data	DNNs and LSTM for SoC prediction, RF for SoH estimation	High accuracy: DNN Mean Squared Errors (MSE) of 7.6E-4, LSTM MSE of 0.023, SoH RF accuracy of 92%	Validation limited to a single drone setup, potential overfitting
[12]	2023	Develop a clustering approach for optimizing IoT network lifetime by predicting battery SoH	NASA's Prognostic Data Repository	Predict impact of cluster head elections on SoH of batteries before implementing the clustering process	Improved network lifetime and extended number of recharging cycles, outperforming conventional energy-efficient strategies	Dependent on the accuracy of SoH predictions and specific to the dataset used
[13]	2022	Predict battery life for IoT applications powered by renewable energy, focusing on battery prediction problems and joint access control	IHEPC	Hybrid algorithm combining LSTM and PCA. HQN with LSTM for access control and two-layer LSTM deep Q-network network for battery prediction and joint access control solutions	Outperformed traditional algorithms (kNN, RF, SVM) with about 92% error minimization. Improved network performance and effectiveness compared to similar methodologies	Requires further testing on larger dimensional datasets. Needs validation in diverse IoT environments.
[14]	2022	Develop a BMS using IoT, enhanced with a prediction algorithm based on ML for predicting SoC and SoH	Battery usage and performance data collected via IoT sensors	Application of a ML algorithm to predict SoC and SoH	Proposed BMS can effectively predict SoC and SoH with high accuracy	Need for a more diverse dataset and evaluation under different environmental conditions
[15]	2021	Develop a data-driven prediction model for the RUL of lithium-ion batteries, focusing on robust generalization across datasets.	NASA randomized dataset and center for advanced life cycle engineering dataset for source domain cells	Employ a novel auto-CNN-LSTM architecture combining CNN and LSTM networks to capture temporal degradation patterns	Achieve a MAPE of 5.342% for RUL prediction, indicating practical applicability.	Dataset limitations in terms of variability may affect the model's generalization. Suggest the need for more diverse datasets.
[5]	2021	Introduce a DNNwMF to predict the RUL of lithium-ion batteries	Datasets from NASA's Prognostic Center of Excellence and the University of Maryland	Use an autoencoder and DNN with memory features to optimize online training, reducing dimensions and optimization parameters	Incorporating memory features significantly improved RUL prediction accuracy, with RMSE more than halving compared to models without memory features	Increased number of optimization parameters with input features, accuracy improvement with encoding dimensions, trade-off between complexity and performance
[8]	2020	Develop a predictive model for forecasting battery replacement needs in IoT services	'Beach Water Quality – Automated Sensors' dataset in Chicago	Employ ML techniques, particularly RF regression algorithm	High predictive accuracy of 97%, effective in forecasting battery replacement needs	Limited to the dataset used, may not generalize to all battery types.
[1]	2020	Address the need for accurate and secure processing of data from IoT devices by proposing a framework using DNNs and blockchain.	Real-time data from various sensors at the beach of Chicago Park District	Train a DNN model to predict battery life and store predictions on the blockchain for decentralized and secure storage.	Achieve high accuracy in predicting battery life.	Need for further validation on larger and more diverse datasets. Computational overhead associated with blockchain technology.

III. METHODOLOGY

The methodology section of this review paper begins with a systematic search of academic databases, including IEEE Xplore, ScienceDirect, and Google Scholar, using relevant keywords to identify papers published between 2020 and 2024. The choice of papers was based on those that had a direct relation to the projection of battery life in IoT networks with particular emphasis on those involving predictive modeling techniques and ML algorithms. After that, information that included authorship, objectives, datasets, methodologies, results, and future directions was extracted from each paper. After that, data was analyzed to determine typical modes and patterns of battery life prediction models of IoT Networks. Together, we synthesized the key findings from each paper to give an overall picture of the most current trends. Finally, the methodology section reviews why it is important to predict the health of the battery as soon as possible and presents gaps in the existing literature. This paper also gave recommendations on future directions to help direct the research community towards solutions that could potentially be more resistant to adversarial attacks while still able to save battery life for IoT networks. Lastly, sections were formatted for the review paper, and drafts of the review paper were composed and revised to create a logical, coherent, and accurate presentation and synthesis of the literature review.

IV. PERFORMANCE PREDICTION MODELS

Performance prediction models are crucial in the IoT to ensure the quality of service and optimize network performance. Theoretical models to predict IoT applications, networks, and services to estimate performance bottlenecks, optimal sleep/wake-up schedules, and application-aware performance management [16]. Traditional techniques such as RF, queuing network modeling, and linear regression (LR) are used; but new methods like LSTM models have also been used in predicting the network performance of IoT systems using time series IoT data. Performance evaluation for these approaches done by examining explained variation (R2), Brier score, and area under the receiver operating characteristic (ROC) curve (AUC). Various IoT applications have employed these models including medical diagnosis, student performance prediction, and genetic variation prediction aimed at accurate forecasts and informed decisions [8].

V. BATTERY LIFE IN IOT NETWORKS

One important factor in IoT networks is battery life; the performance of devices is ensured by their battery life and longevity. In typically unwired environments like forests and plantations, some IoT devices can be located to such an extent that battery replacement or recharging is simply a physically impossible task. Manufacturers together with end-users must accurately estimate the battery life to maintain the performance of commercial products by understanding the power consumption of all components (such as RF radios, displays, beepers, vibrators, etc.). Bottom Up Seeking for new top-down approaches, Optimizing Hardware (Power efficient integrated circuit), Software and examining Low Power Design techniques, Hardware, and Software to configure components, reducing power consumption, keeping power integrity along with each component of the SOC, Power Management Techniques, Efficient Communication Protocols, Onboard active components, Software-level optimization [16]. There are a few other factors, like temperature, system design, power considerations, transmission frequency, and network protocols, which all impact battery life. Failure to use the option for periodic updates can have a huge impact on battery legibility. Beyond the operational convenience, a longer-life battery offers irrefutable benefits as it relates to data reliability, maintenance efficiency, and environmental sustainability of IoT sensors. By prioritizing submetering solutions that strive to keep a lower impact on battery life, property managers can find a harmony of efficiency and reliability while at the same time promoting both the longevity of batteries and an improved approach to sustainability in their property management operations [8].

VI. ESTIMATION OF BATTERY LIFE FOR IOT NETWORKS USING PERFORMANCE PREDICTION MODELS

The Estimation of battery life for IoT networks using performance prediction models is a crucial aspect of ensuring the reliability and sustainability of these networks. Several studies have been conducted to develop and evaluate ML and deep learning techniques.

A. Linear Regression (LR)

LR is a statistical technique used to predict a continuous output variable based on one or more input variables. For battery life prediction in IoT networks, LR can assist in establishing a correlation between inputs such parameters as the type of the network, type of sensor data and environmental details, and the longevity of IoT devices [8].

B. Random Forest (FR)

RF is one of the methods used in artificial intelligence, and it comprises several decision trees. Multiple decision trees are built from the dataset throughout training and are integrated to make predictions based on an average majority vote rule. Hence, several are its functions include variable selection, classification as well and regression duties. RFs select features randomly for each tree decision, focusing on essential features; this feature selection mechanism is RFs' parameters, such as the number of trees or features. It is internally implemented using cross-validation and is adequate in addressing non-linear internal perceptions of the data [8].

C. Deep Neural Networks (DNNs)

DNNs are increasingly being utilized for battery life prediction in IoT networks due to their ability to capture complex patterns in data. In this backdrop, DNNs are trained to employ earlier data inclusive of battery concerning usage, environmental conditions, device activities, etc., to identify underlying correlations and emerge prospects of battery discharge in the process. Evaluating several inputs and their impact on battery performance, DNN gives accurate predictions that will help in the management of IoT devices and foremost optimization of energy consumption strategies for everlasting battery lives [5].

D. XGBoost Regression

The XGBoost regression model is an implementation of an ensemble technique that is widely used to solve problems quickly and accurately across a range of domains; classification and ad-click rate are examples. Kaggle competitions have always thrived for this strong learning technique as it is not only robust but performant as well. XGBoost applies a boosting technique where trees are built successively in a way to reduces the error made by the previous tree. Its features include regularization, efficient management of sparse data and weights, parallel learning, and out-of-core learning. That is highly valuable for dealing with large data sets which cannot be entirely stored in memory [8].

E. Artificial Neural Networks (ANNs)

ANN is popular and central in designing and implementing of IoT networks; in other words, ANN is critical to predicting battery life. Although charging patterns, or degrees of inter_battery discharge, temperature fluctuations, and other battery signatures can seem random to the human eye, ANNs can recognize such complex relationships and will be able to give good estimates about battery life based on historical data. Consequently, these models enable IoT network managers to effectively allocate resources such as manpower and funds and schedule the maintenance of IoT devices and networks in a way that can enhance and extend the practical functionality of IoT devices as well as increase reliability and reliability of the IoT networks in their usage area for different applications [8].

F. Principle Component Analysis (PCA)

PCA is an approach that is used to estimate the lifetime of batteries in IoT networks. PCA helps to reduce data dimensionality through the identification of major features. Through the extraction of important attributes and elimination of redundancies, it increases the knowledge of underlying patterns as well as relationships so existing within the data set. This process not only simplifies data but also enhances the performance and accuracy of battery life prediction models for IoT networks [13].

G. Standard Scalar Normalization

Standard scalar normalization is essential in the battery life prediction for IoT networks. It is a process of normalizing your features by subtracting the mean and scaling to unit variance. Data Normalization increases the throughput and the scale of the prediction algorithm. This guarantees that all characteristics affect equally to the prediction/output which means a better estimation of the IoT network's battery life [8].

H. Long Short-Term Memory (LSTM)

Predicting battery life in IoT networks has become popular in the research being done using time series data because LSTM networks are capable of handling sequential data and taking advantage of learning long-term dependencies. It uses training data for battery discharge profiles to train LSTM models considering the effects of device usage, power modeling, and environmental factors. LSTM networks, by use of their ability to learn from the past sequences of data, provide a way to predict the future battery life hence enabling proactive maintenance and resource allocation in IoT networks. This predictive capability improves the overall system efficiency and long-term operation of IoT devices [13].

I. Convolutional Neural Networks (CNNs)

This has burned a use case where CNNs are used to predict battery life in IoT networks. This app uses CNNs for feature automatic learning of data presented (e.g., sensor readings or historical battery drain patterns). CNNs learn the intricate dependencies present in the battery discharge rates, environmental factors, and usage patterns by training on related datasets, and in turn, they can forecast the battery life as well. This improves the management of energy in IoT networks, and therefore, using resources effectively and extends the life of the device [15].

VII. DISCUSSION

Finally, this study summarized the various performance prediction models of battery life in IoT networks, hence, shedding light on a broad spectrum of approaches that provide an individual advantage and shortcomings. LR, simple to understand and interpret, is seen as a basic type of model used to predict the battery duration given its input constituents. This capability is very powerful, but its nature as a vector space makes it suitable for a low-dimensional representation, which may be a limitation in encoding all the relevant information in an IoT environment due to its strong linear assumptions. On the other hand, RF are very good at detecting nonlinear relationships and interactions between features, which makes it a sound choice for the intricate nature of IOT data. However, these can also need hyperspace specialization and fail in generalized outside of the training data. While DNNs are incredibly flexible in modeling complex patterns, their black-box property could result in interpretability issues. XGBoost regression, renowned for its accuracy and efficiency, may require tuning to prevent overfitting and struggle with missing data.

Likewise, some optimizations like ANNs are adaptable but need heavy computational power and tuning. This is a good use case for PCA which can be used to reduce dimensions but can lose all information too. Standard Scalar Normalization provides stability to the model but depends on Gaussian Distributions While LSTM networks are very suitable for modeling dependencies over time, they require a longer history of sequential data, as well as tuning. Even where CNNs do contain spatial dependencies, they can fail to capture long-range correlations. This is a brief introduction of the best models in terms of the advantages and disadvantages, in such a way that helps an easier and more informed decision-maker when predicting battery life on the IoT network. The summary of strengths and weaknesses related to the prediction model to evaluate battery life in IoT networks has been provided in Table II.

TABLE II
SUMMARY OF STRENGTHS AND WEAKNESSES RELATED TO THE PREDICTION MODEL TO EVALUATE BATTERY LIFE IN IOT NETWORKS.

Models	Strengths	Weaknesses
LR	Simple and easy to interpret; provides a basic framework for predicting battery life based on input features	Limited by linear assumptions, which may not capture the complexities of IoT environments and interactions
RF	Captures non-linear relationships and interactions among features; robust against overfitting and works well with large datasets	Requires careful tuning of parameters; may struggle with extrapolation beyond the training data range
DNNs	Highly flexible and capable of capturing complex, nonlinear patterns in the data; can model intricate dependencies	Black-box nature makes them difficult to interpret; require significant computational resources and extensive training data
XGBoost Regression	High accuracy and efficiency; effective in handling various types of data and preventing overfitting through regularization techniques	Needs extensive parameter tuning to optimize performance; may struggle with handling missing data
ANNs	Flexible and capable of modeling complex, nonlinear relationships; suitable for large and varied datasets	Requires significant computational resources and extensive tuning of hyperparameters; prone to overfitting without proper regularization
PCA	Reduces data dimensionality, making it easier to handle and visualize; helps in eliminating multicollinearity	May discard valuable information by focusing only on the principal components, potentially leading to loss of important details
Standard Scalar Normalization	Enhances model stability by standardizing feature scales; helps in achieving faster convergence during training	Assumes Gaussian distributions, which may not be true for all data types; less effective for non-Gaussian distributed data
LSTM	Excels in modeling temporal dependencies and sequences, making it ideal for time-series data and sequential predictions	Requires large amounts of sequential data for training; involves complex architecture and tuning processes
CNNs	Effectively captures spatial dependencies and patterns; excels in image data and spatial feature extraction	May struggle with capturing long-range dependencies and correlations; often requires large datasets and significant computational power

VIII. CONCLUSION AND FUTURE DIRECTIONS

In conclusion, the paper has shown various performance prediction models for battery life in IoT networks and how it is important to predict them early to optimize network performance and lifespan. The strengths and drawbacks of these predictive models are given by summarizing the main findings, methodologies used, and their applications. However, battery management in IoT devices can be a challenging task because of variations in power consumption and external factors that affect them. Recently though there have been great improvements in predictive modeling methods, still more research is needed to overcome some limitations of current techniques hence making IoT systems sustainable.

In the future, the directions for research must be focused on advancing battery life prediction in IoT networks by improving their key areas. To start with, more precise and dependable models of prediction need to be designed for IoT applications due to specific attributes as well as constraints of IoT equipment. This might involve looking into alternative ML algorithms like reinforcement learning and meta-learning so that predictions can be made more accurate and applicable in different situations. Furthermore, interdisciplinary cooperation between scientists, practitioners, and industrial players will help these predictive models transform into real-world applications. For example, standardizing evaluation metrics, creating benchmark datasets, and establishing open-access repositories for sharing models and data will enable information exchange thus leading to an increased rate of innovation in this area. Finally, rigorous validation studies should occur within different IoT environments to test the validity and scalability of predictive models that are meant to make better IoTs more competitive at a global level.

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