Available Online at www.ijcsmc.com

International Journal of Computer Science and Mobile Computing

A Monthly Journal of Computer Science and Information Technology

ISSN 2320–088X
IMPACT FACTOR: 7.056

IJCSMC, Vol. 12, Issue. 5, May 2023, pg.1 – 6

Battery Management System for Analysing Accurate Real Time Battery Condition using Machine Learning

Arunadevi R[1]; Saranya S[2]; Bharkavi M[3]; Nirogini S[4]; Prapthi N[5]
[1,2,3,4,5]Department of Computer Science and Engineering & Parisutham Institute of Technology & Science, Thanjavur, India
[1] aruna.ap.cse.pits@gmail.com; [2] saranyasaravanan1008@gmail.com; [3] bharkavi19m@gmail.com;
[4] glorygideon77@gmail.com; [5] prapthi2001@gmail.com
DOI: https://doi.org/10.47760/ijcsmc.2023.v12i05.001

Abstract: **The energy storage system is one of the essential components of Electric Vehicles (EV) that is anticipated to penetrate the current transport market because of the constant increase in environmental pollution and prices. Most EVs use lithium-ion batteries as their source of power. Lithium-ion batteries are rechargeable batteries that are typically used to power portable devices and EVs as well as Hybrid Electric Vehicles (HEVs) (powered both by fuel and electricity). The battery performance degrades progressively with time leading to some potential disasters. Current approaches for data-driven fault prediction provide good results on the exact processes they were trained on but here the batteries often lack the ability to adapt to flexibly change. To overcome the problem, here use Sequential learning which promises flexibility, allowing for an automatic adaption of previously learned knowledge to new tasks. Thus, it provides the State of Charge (SoC) of the battery and predicts its condition, which gives highly accurate results.**
Keywords: Lithium-ion batteries, Electric vehicles, Sequential Learning, State of Charge.

I. INTRODUCTION

An Electric Vehicle Battery (EVB, also known as a traction battery) is a battery used to power the electric motors of a Battery Electric Vehicle (BEV) or HEV. These batteries are usually rechargeable batteries and are typically Li-ion batteries. These batteries are specifically designed for a high ampere-hour (or kilowatt-hour) capacity. EV batteries differ from Starting, Lighting, and Ignition (SLI) batteries as they are designed to give power over sustained periods and are deep-cycle batteries. Batteries for EVs are characterized by their relatively high power-to-weight ratio, specific energy, and energy density; smaller, lighter batteries are desirable because they reduce the weight of the vehicle and therefore improve its performance. Compared to liquid fuels, most current battery technologies have much lower specific energy, and it often impacts the maximum all-electric range of the vehicles. The most common battery type in modern EVs is lithium-ion and lithium polymer, because of their high energy density compared to their weight. Other types of rechargeable batteries used in EVs include lead–acid ("flooded", deep-cycle, and valve-regulated), nickel-cadmium, nickel–metal hydride, and, less commonly zinc–air batteries. The amount of electricity (i.e. electric charge) stored in batteries is measured in ampere-hours or coulombs, with the ampere-hours often measured in kilowatt-hours. Since the late 1990s, advances in lithium-ion battery technology have been driven by demands from portable electronics, laptop computers, mobile phones, and power tools. The BEV and HEV market place has reaped the benefits of these advances both in performance and energy density. Unlike earlier battery chemistries, notably nickel-cadmium, lithium-ion batteries can be discharged and recharged daily and atany SoC. The battery pack makes up a significant cost of a BEV or an HEV. As of December 2019, the cost of EVB has fallen 87% since 2010 on a per kilowatt-hour basis. As of 2018, vehicles with over 250 mi (400 km) of all-electric range, such as the Tesla Model S, have been commercialized and are now available in numerous vehicle segments In terms of operating costs, the price of electricity to run a BEV is a small fraction of the cost of fuel for equivalent internal combustion engines, reflecting higher energy efficiency.

II. LITERATURESURVEY

Continual Reinforcement Learning Using Real-World Data for Intelligent Prediction of SoC Consumption in EV, this paper aims to accelerate migration towards EV and presents several problems to solve. The main appearance aims at the management and prediction of the SoC in real long-range routes of different variations in altitude for a more eminent energy consumption and vehicle recharge plan. This paper presents the implementation of a new algorithm for SoC estimation based on continuous learning and Meta-Experience Replay (MER) with a reservoir sample. It combines the Reptile meta-learning algorithm with the experience replay technique for stabilizing the reinforcement learning. the suggested algorithm considers several important factors for the prediction of the SoC in EVs such as speed, travel time, route altimetry, consumed battery capacity, and regenerated battery capacity. State of Power Prediction for Lithium-Ion Batteries in EV via Wavelet- Markov Load Analysis, with the development of Electric Drive Vehicles (EDVs), the SoC estimation for Lithium-Ion (Li-ion) batteries has become increasingly more important. Based on the analysis of some of the most popular model-based SoC estimation methods, the Proportional-Integral (PI) observer is proposed to estimate the SoC of lithium-ion batteries in EDVs. The structure of the proposed PI observer is analyzed, and the convergence of the estimation method with model errors is verified. To demonstrate the superiority and compensation properties of the proposed PI observer, the simple-structure RC battery model is utilized to model the Li-ion battery. To validate the results of the proposed PI-based SoC estimation method, the experimental battery test bench is established. In the validation, the Urban Dynamometer Driving Schedule (UDDS) drive cycle is utilized, and the PI-based SoC estimation results are found to agree with the reference SoC, generally within the 2% error band for both the known and unknown initial SoC cases.

III. PROPOSEDSYSTEM

It provides Sequential learning which promises flexibility, allowing for an automatic adaption of previously learned knowledge to new tasks. Sequential learning is lifelong learning which continuously learns and evolves based on the input increasing amount of data while retaining previously learned knowledge. First Process, collecting the appropriate datasets from the research websites. A battery dataset is used to produce SoC. After the datasets are collected, the principle component analysis (PCA) techniques are used for dataset preprocessing. Then, it will be fed for training with the machine learning algorithm such as Extreme Gradient Boosting (XGB) regression and it will validate and evaluate the datasets. Precise SoC estimation can avoid unpredicted system interruption and prevents the battery from being overcharged and over-discharged, which may cause permanent damage to the internal structure of batteries. Thus, it project provides information such as the SoC of the battery to determine the condition of the battery.

IV. SYSTEMARCHITECTURE

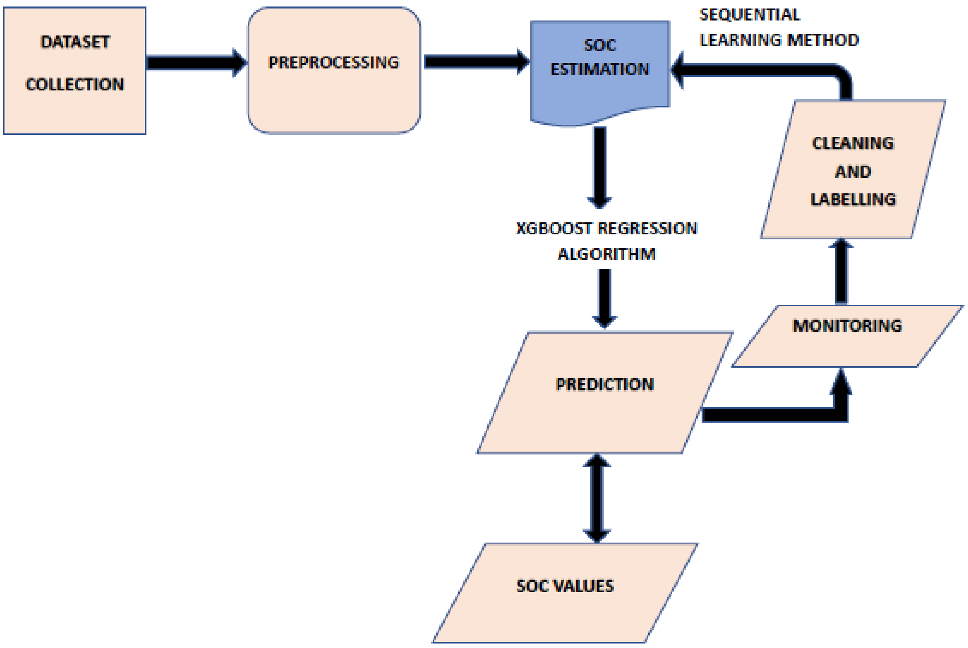

Fig.1 Architecture Diagram

A system architecture can consist of system components and the sub-systems developed, that will work together to implement the overall system. There have been efforts to formalize languages to describe system architecture; collectively these are called Architecture Description Languages (ADLs). Fig.1 specifies the components of the proposed system. A Data Flow Diagram (DFD) maps out the flow of information for any process or system. It uses defined symbols like rectangles, circles, and arrows, plus short text labels, to show data inputs, outputs, storage points, and the routes between each destination.

MODULE DESCRIPTION

Data preprocessing is a data mining technique that transforms raw data into an understandable and readable format. The PCA is a popular unsupervised learning technique for reducing the dimensionality of data. It increases interpretability yet, at the same time, it minimizes information loss. It helps to find the most significant features in a dataset and makes the data easy for plotting in 2D and 3D. PCA helps in finding a sequence of linear combinations of variables. The Principal Component is a straight line that captures most of the variance of the data. They have a direction and magnitude. Principal components are orthogonal projections (perpendicular) of data onto lower-dimensional space.

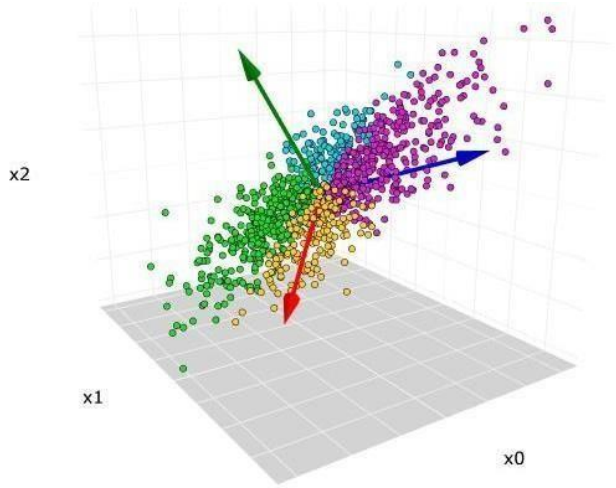

Fig.2 Data Pre-Processing

A. Training using a Machine Learning algorithm

It will be fed for training with the machine learning algorithm such as XGB regression. XGBoost is an open-source library that provides an implementation of the gradient boosting algorithm. Shortly after its development and initial release, often the key component in winning solutions for a range of problems in machine learning competitions. Regression predictive modeling problems involve predicting a numerical value such as a dollar amount or a height. It can be used directly for regression predictive modeling.

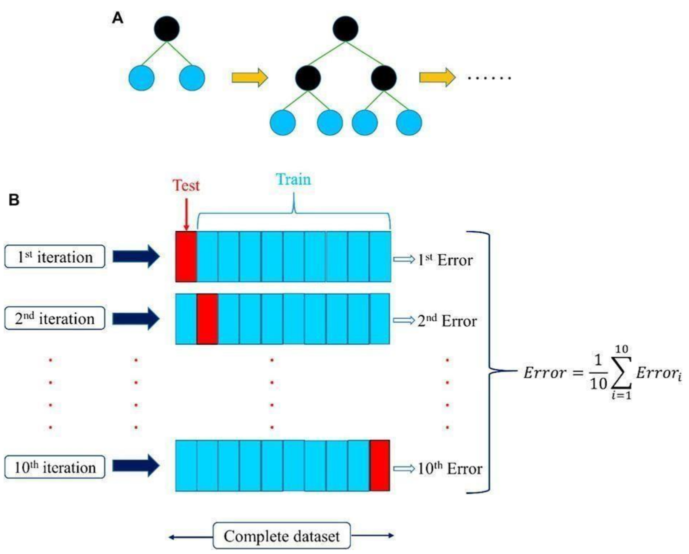

Fig.3 Training Data

B. Validation and Evaluation

After training with the XGB regression algorithm, it will validate and evaluate the datasets. Validation in machine learning is like authorization or authentication of the prediction done by a trained model. While on the other hand, evaluation in machine learning refers to the assessment or test of the entire machine learning model and its performance in various circumstances. It involves assessment of the machine learning model training process, Machine learning algorithms performance, and how accurate the predictions are given in different situations.

C. Prediction of SoC and applying continuous learning method

After validation and evaluation, A battery dataset is used to produce SoC. Estimating SoC can avoid unpredicted system interruption and prevents the battery from being overcharged and over-discharged, which may cause permanent damage to the internal structure of batteries. Then, applying the Sequential learning method which is used for decreasing the error rate. It provides the results as an accurate estimation of the SoC of the battery and enhances the prediction on each cycle of training

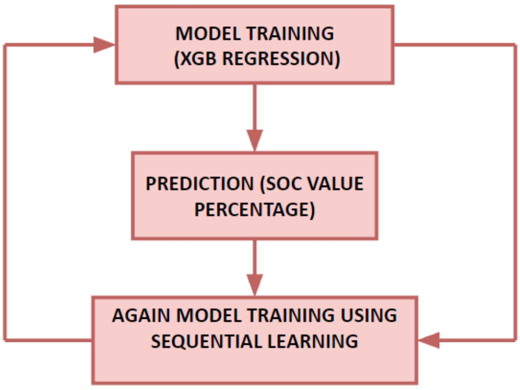

Fig.4 *Prediction of SoC*

V. CONCLUSION AND FUTURE WORK

The project has been implemented to predict the accurate estimate of the SoC of the battery using the machine learning algorithm and display the generated result to the user. The Machine Learning Algorithm such as XGB Regression is used to predict the outcome of the SoC battery. It also helps in improving the battery life and performance eventually and prevents the battery to become worse. The battery can be implemented in EV and battery industries. The automobile industry this time, with EVs becoming the country's favourite. In the last two years, the number of two- and three-wheeled electric cars on Indian roadways has risen substantially. The Indian Government endeavors and plans to convert a large percentage of automobiles on the Indian roads to EV. Over the past years, the energy storage sector has seen continued development and adoption of new and advanced chemistries and technologies. Li-Ion Batteries have been one of the most recent adopters and based on their chemistry, performance, and features became preferred and looked upon technology. Li-ion batteries have changed the way products are designed in modern times. At the same time, Solid-state batteries play a crucial role in lightening the load of lithium-ion and lithium polymer batteries by combining the versatility, safety, and flexibility that are usually associated with conventional systems with higher performance without sacrificing much of their properties. In the coming future, the application of the project in the EV field can promote detecting the state of the battery's health with more accuracy in the next phase. In the EV field, they have more choices to develop or convert the project in many ways. Thus, the project has an efficient scope in the coming future where manual predicting can be cheaply converted to computerized production.

REFERENCES

[1]. BinGou; YanXu; XueFeng, State-of-Health Estimation and Remaining-Useful-Life Prediction for Lithium-Ion Battery Using a Hybrid Data-Driven Method, IEEE Transactions on Vehicular Technology (Vol no:69,2020)

[2]. Carkhuff, B.G., Demirev, P.A. and Srinivasan, R. (2018). Impedance-Based Battery Management System for Safety Monitoring of Lithium-Ion Batteries. IEEE Transactions on Industrial Electronics, 65(8), pp.6497–6504. doi:10.1109/tie.2017.2786199.

[3]. Carter,R., Cruden,A. and Hall,P.J.(2012). Optimizing for Efficiency or Battery Life in a Battery/Super capacitor Electric Vehicle. IEEE Transactions on Vehicular Technology, 61(4), pp.1526–1533. doi:10.1109/tvt.2012.2188551.

[4]. Corno,M. and Pozzato,G. (2019). Active Adaptive Battery Aging Management for Electric Vehicles. IEEE Transactions on Vehicular Technology, pp.1–1. doi:10.1109/tvt.2019.2940033.

[5]. Elsayed,A.T., Lashway,C.R. and Mohammed,O.A.(2015). Advanced Battery Management and Diagnostic System for Smart Grid Infrastructure. IEEE Transactions on Smart Grid, pp.1–1. doi:10.1109/tsg.2015.2418677.

[6]. JunXu; Chunting Chris Mi; Binggang Cao; Junjun Deng; Zheng Chen; Siqi Li, The SoC Estimation of Lithium-Ion Batteries Based on a Proportional-Integral Observer, IEEE Transactions on Vehicular Technology(Volno:63,2014)

[7]. Martinez-Laserna, E., Sarasketa-Zabala, E., Villarreal Sarria, I., Stroe, D.-I., Swierczynski, M., Warnecke, A.,Timmermans, J.-M., Goutam, S., Omar, N. and Rodriguez, P. (2018). Technical Viability of Battery

Second Life: A Study From the Ageing Perspective. IEEE Transactions on Industry Applications, 54(3), pp.2703–2713. doi:10.1109/tia.2018.2801262.

[8]. ORTIZ,J.P., AYABACA,G.P., CARDENAS,A.R., CABRERA,D. and Valladolid,J.D.(2022). Continual Refoircement Learning Using Real-World Data for Intelligent Prediction of SoC Consumption in Electric Vehicles. IEEE Latin America Transactions,20(4),pp.624–633.doi:10.1109/tla.2022.9675468.

[9]. Pandzic, H. and Bobanac, V. (2019). An Accurate Charging Modelof Battery Energy Storage. IEEE Transactions on Power Systems,34(2),pp.1416–1426.doi:10.1109/tpwrs.2018.2876466.

[10]. Sanz-Gorrachategui, I., Pastor-Flores, P., Pajovic, M., Wang, Y., Orlik, P.V., Bernal-Ruiz, C., Bono-Nuez, A. and Artal-Sevil,J.S. (2021). Remaining Useful Life Estimation for LFP Cells in Second-Life Applications. IEEE Transactions on Instrumentation and Measurement, 70, pp.1–10. doi:10.1109/tim.2021.3055791.

[11]. Thirugnanam, K., Kerk, S.K., Yuen, C., Liu, N. and Zhang, M. (2018). Energy Management for Renewable Microgrid in Reducing Diesel Generators Usage With Multiple Types of Battery. IEEE Transactions on IndustrialElectronics,65(8),pp.6772–6786.doi:10.1109/tie.2018.2795585.

[12]. Xiong, R., Zhang, Y., Wang, J., He, H., Peng, S. and Pecht, M. (2018). Lithium-ion battery health prognosis based on a real battery management system used in electric vehicles. IEEE Transactions on Vehicular Technology, pp.1–1.doi:10.1109/tvt.2018.2864688.

[13]. Xu, B., Oudalov, A., Ulbig, A., Andersson, G. and Kirschen, D.S. (2018). Modeling of Lithium-Ion Battery Degradation for Cell Life Assessment. IEEE Transactions on Smart Grid,9(2),pp.1131–1140. doi:10.1109/tsg.2016.2578950.

[14]. Zhiqiang Lyu; Renjing Gao; Lin Chen, Li-Ion Battery State of Health Estimation and Remaining Useful Life Prediction Through a Model-Data-Fusion Method, IEEE Transactions on Power Electronics (Volno:36,2021)

[15]. Zhu, C., Lu, F., Zhang, H., Sun, J. and Mi, C.C. (2018). A Real-Time Battery Thermal Management Strategy for Connected and Automated Hybrid Electric Vehicles (CAHEVs) Based on Iterative Dynamic Programming. IEEE Transactions on Vehicular Technology, 67(9), pp.8077–8084. doi:10.1109/tvt.2018.2844368.

