Journal of New Materials for Electrochemical Systems
Vol.27, No.2, June 2024, pp. 86 - 98
Journal homepage: http://iieta.org/journals/jnmes

An Efficient Li-ion Battery Management System with Lossless Charge Balancer for RUL and SoH Prediction

Alexprabu, S.P.[1*], Sathiyasekar[2]

[1*]S.A. Engineering College, Thiruverkadu, Chennai-77
[2]K.S.R. Institute for Engineering and Technology, Erode, Tamilnadu, India.

Corresponding Author Email: [1*]scholar.alexprabusp@gmail.com

https://doi.org/10.14447/jnmes.v27i2.a02

Received: November 20, 2023
Accepted: March 30, 2024

Keywords:
Battery management system, Adaptive Matrix Switch Algorithm, Unscented Kalman Filter, Adaptive Neuro-Fuzzy Inference network, Grey Wolf Optimizer.

ABSTRACT

Electric vehicles (EV) employ batteries to generate their mechanical power for transportation, but the main challenge is to improve the battery management system (BMS) and increase the lifespan of the EV battery. In the existing battery management system, energy loss during charge balancing operation and prediction errors happens in remaining useful life (RUL) and state of health (SoH). Hence a novel Efficient Li-ion Battery Management System with Lossless Charge Balancer for RUL and SoH Prediction is proposed to improve the Battery Management System (BMS) and lifespan of the EV battery. The existing battery management systems have various cell-balancing approaches, but the energy losses in the form of heat create unavoidable instant charge imbalance. Thus, a novel Optimized Multi Input Multi Output-Bi Directional Long Short-Term Memory (MIMO-Bi-LSTM) has been proposed, in which the MIMO-Bi-LSTM Unit is providing better SoC estimation of each cell, and the FFOA (Fruit Fly Optimization Algorithm) is utilized in this state of charge (SoC) estimation of battery and improved accuracy. Moreover, an Adaptive Matrix Gate Switch Balancer is introduced in which the Adaptive Matrix Switch Algorithm is used to avoid charge imbalance and the DGTO (Duplex Gate Turn-Off Thyristors) switches reduce the energy loss during switching and improving the cell life cycle. Furthermore, the existing technique did not consider the variation of the EV motor’s efficiency that changes throughout the operation and the motor terminal resistance which also affects the cycle life of the battery. So, the novel Optimized UK-ANFI Network is introduced in which a UK (Unscented Kalman) Filter eliminate the non-linearity in the measured values of parameters and the ANFI (Adaptive Neuro-Fuzzy Inference) Network receives the linearized data and predicts the RUL and SoH of the battery pack. Then a GWO (Grey Wolf Optimizer) minimize prediction errors and provide better life cycle prediction. The result obtained by the proposed model have low RMSE in RUL and SoH prediction, high accuracy and low prediction time.

1. INTRODUCTION

Due to their high energy conversion efficiency and lack of greenhouse gas emissions, electric vehicles are quickly gaining favour in modern transportation as a result of the growing emphasis on environmental protection and the reaction to the global energy crisis. The battery energy storage system (BESS) is a crucial part of electric vehicles and has recently drawn more attention since it plays a significant role in driving performance, safety, and range. Due to their high specific energy, small size, and low self-discharge rate, lithium-ion batteries (LIBs) are typically used in BESS. To guarantee the longevity, power, and security of LIBs, the main purpose of the BMS is to efficiently control and manage the battery. The battery cell and battery pack signal measurements, state estimation, battery pack consistency evaluation, battery pack balancing, safe charging, fault detection, and thermal management are examples of typical functions. The evolution of BMS into the following generation is currently in the advanced management stage. The battery state estimation approach has low adaptability in harsh conditions as a result of the growing battery population and higher energy density of batteries, and the safety concern with batteries is becoming more and more obvious. Consequently, the creation of the following generation of BMS with intelligence is about to happen [1-4].

The battery management system continuously checks the battery's performance to guarantee the car runs without a hitch. Battery temperature, current, voltage, SoC, and SoH are the primary monitoring statuses. The SOC is defined as the percentage of the battery charge left and the highest possible capacity; these important elements interact with one another. When SOC is accurately estimated, overcharging and over-discharging are prevented, which is essential for extending battery life and ensuring the effective operation of electric cars. However, the explanation for SOC's complex internal states, such as battery cell temperature, electrochemical reaction process, battery ageing, and internal material states, is primarily dependent on these complex internal states. The internal battery states cannot be directly monitored, and can only be inferred and anticipated by the use of a limited set of signals, such as voltage, current, and temperature signals, as is the case with the majority of electrochemical energy storage systems [5-8].

The internal states of the battery have a very nonlinear relationship with the externally observed signals as a result of the intricate electrochemical reaction occurring inside the battery. This problem is made worse by complex or demanding operating conditions. Additionally, the battery degradation during the cycle affects the state estimation accuracy and makes it more challenging. Since battery performances is change with ageing and a stable and exact estimation is needed for the entirety of the battery life, accurate battery state estimation is still a technical challenge. Lithium-ion batteries' performance will degrade during the continuous charging and discharging process as their capacity and impedance decrease. This is lead to battery faults like internal short circuits and thermal runaway, which cause catastrophic accidents and equipment failure. To increase the battery's dependability, it is crucial to precisely measure the battery's SoH and predict its RUL. The battery's health status is clearly seen in the capacity change that occurs over its life cycle. As a result, the ability has been used extensively to define SOH and RUL indicators. A Li-ion battery is typically considered to have failed when its capacity declines by 20–30% of the rated values [9-12].

SOH and RUL were mostly determined in the early Li-ion battery applications using impedance measurement using a probe. However, this method required a pricey apparatus and took a lot of time. As a result, methods such as discharge to a specified cut-off voltage, open-circuit voltage, voltage under load, battery temperature, and the amount of float charge have been used to assess the battery capacity indirectly. Both model-based and data-driven strategies have been used in recent years to forecast SOH and RUL. The model-based approaches call for the creation of a battery deterioration model that strikes a balance between complexity and accuracy. In actual applications, nevertheless, a variety of variables including environment and load had an impact on these approaches. Furthermore, accurate degenerate models are very challenging to derive due to the relative complexity of the law of physicochemical reactions of Li-ion batteries. Data-driven approaches are a popular area of research since they do not rely on Li-ion battery ageing dynamics models. To accomplish RUL and SOH prediction, they extract the implicit data on the battery health state from a range of experimental datasets [13-15]. Even though there are many advancements in the battery management system of electric vehicles, there are still required many improvements for better estimation of SoC, prediction of remaining useful life and SoH of batteries by eliminating the prediction errors, problems in the charge balancing strategies and other limitations in the present research. Major contributions in this research are given as follows

- In battery management systems in battery packs of electric vehicles, the complexity in SoC estimation due to energy loss during charge balancing is removed by MIMO-Bi-LSTM Unit that receives the parameters of each cell in the battery pack and providing better SoC estimation and the different SoC values of each individual cell SoC values are estimated with high accuracy by FFOA.
- To balance charge in battery management system, adaptive matrix switch algorithm, selects the pairs of cells having a large difference in SoC values thereby avoiding charge imbalance and reduced the energy loss during switching and improving the cell life cycle.
- In the prediction of life cycle of battery, the complexity in predicting RUL and SoH in the battery is removed by UK Filter that eliminate the non-linearity in the measured values of parameters and the ANFI Network receives these linearized data and predicts the RUL and SoH of the battery pack and optimize output parameters with enhanced life cycle prediction.

These contributions have been mentioned considered for solving the problems in charge balancing in each cell of the battery and prediction of RUL and SoH in the existing methods. The Content of the research is organized as section 2 describes the literature survey, section 3 describes the proposed methodology and its working process, and section 4 discusses the proposed model evaluation, performance, and comparative analysis. Finally, section 5 concludes the research.

2. LITERATURE SURVEY

Kyungnam Park et al [16] offered a new long short-term memory (LSTM)-based RUL prediction algorithm in which a variety of quantifiable variables were used from the battery management system, such as the voltage, current, and temperature charging profiles, which patterns change with battery ageing, to estimate RUL even in the presence of the capacity regeneration phenomenon. They used a many-to-one structure instead of the conventional LSTM prediction, which matches the input layer with the output layer as a one-to-one structure that be flexible for different input types and to drastically reduce the number of parameters for greater generalisation. According to the experimental findings, the single-channel LSTM model was superior to the baseline LSTM in terms of mean absolute percentage error (MAPE) by 39.2%. But this approach involved more computational time for generalization.

Shunli Wang et al [17] proposed an enhanced anti-noise adaptive long short-term memory (ANA-LSTM) neural network with high-robustness feature extraction and optimal parameter characterisation for reliable RUL prediction on the basis of an improved dual closed-loop observation modelling technique. Then, using multiple feature collaboration and characterization of its internal coupling mechanism, an adaptive state parameter feedback correction strategy was built, taking various current rates, ambient temperatures, and other influencing parameters into account. Then, model training and meta-structure fine-tuning were done in tandem with collaborative multi-parameter optimisation. However, the increase in the parameter difference caused variations in the state information of the battery.

Huixin Tian et al [18] suggested a brand-new multimode ensemble support vector regression (ME-SVR) technique to estimate SOC. This method used a clustering algorithm to separate the original data set into various data subsets while taking into account the characteristics of battery data. For each data subset, an SVR estimation model was then created. Finally, the output was produced using the weighted average concept of ensemble learning when the estimation results of various SVRs are merged. According to the experimental findings under various driving scenarios, this unique technique is greatly increase SOC estimating accuracy as well as the model's stability and generalizability. Still, there is a need to improve the clustering algorithm for accurately separating the battery characteristics data.

Zhenhua Cui et al [19] suggested a hybrid approach based on the CNN-BWGRU network in which through the use of a bidirectional network and a "multi-moment input" structure, the method maximises the impact of battery information on the outcomes. The input feature parameters were taught by the convolutional neural network (CNN). Through adjusting the weights, the bidirectional weighted gated recurrent unit (BWGRU) is enhance the network's fitting ability at low temperatures. The suggested network had good robustness, estimation accuracy, and generalisation capabilities. To test the network's believability, the SOC estimate was carried out under a variety of circumstances. The results of the experiments demonstrated that the approach was more accurate and stable than other networks. However, the generalization ability needs to be improved further.

Zuolu Wang et al [20] developed a parameter identification method based on the dynamic voltage responses in the practical constant current (CC) discharging process that identify the battery model parameters using the particle swarm optimisation (PSO) approach. A hybrid SOC estimate method was also suggested to reduce system errors brought on by the model, algorithm, and measurement system. The improved extended Kalman filter (EKF) approach with designed compensating error was used in the suggested hybrid method to suppress system errors. PSO was once more used to calculate the dynamic compensation error using the ampere-hour counting (AHC) method's dependable increase over the whole SOC range. However, the estimation results strongly depended on the initialization of the parameters of the battery.

Kuo Yang et al [21] proposed a deep learning strategy based on a dual-stage attention mechanism to increase SOC prediction accuracy and lessen the impact of noise. It integrated elements from the realm of lithium-ion batteries, such as current, voltage, and temperature, into an encoder-decoder network based on a gated recurrent unit. They pre-processed the attention mechanism's input data during the encoder input stage that enable adaptive feature extraction from the input sequence. Another attention mechanism was employed in the decoder stage to precisely estimate the SOC at the present time, take into account the correlation of the time series, and refer to the preceding encoder's state on the time scale. However, this approach is not handle multiple sequences of input signals with different step lengths which degraded the estimation accuracy.

Yizhao et al [22] improved the partial differential equations with the Laplace transform, Pade approximation, and other techniques, an improved pseudo-two-dimensional electrochemical model is created to determine the transfer function between cell voltage and current. To derive the model temperature dependency, the temperature-sensitive parameters are identified at various temperatures. The temperature-dependent parameters are then extracted for model decoupling. With offline data, the provided model is tested to attain good accuracy over a wide range of state-of-charges and temperatures. Finally, the model is discretized and implemented in the desired algorithm framework in an EV's BMS to validate its effectiveness. However, the interior electrochemical variables are not taken into account, which is reduce the precision of state prediction when the battery ages or the load changes.

Sagar et al [23] analysed the battery's equivalent circuit model (ECM), which depicts the battery's behaviour at various temperatures while taking the battery's internal resistance into account. To ensure that batteries were replaced in a systematic manner based on calendar ageing, a stochastic model for battery ageing and replacement was devised. The Markov chain was used to examine the reliability of EV accessibility and availability. A case research of a diesel-renewable powered Electric Vehicle Charging Station (EVCS) in a micro-grid that meets the need of large-scale EV fleet integration to the grid for power transaction was conducted. The complexity and computing ability of the circuit increase as the number of R-C components rises.

Bruno et al [24] analysed electronic battery management and SoC equalisation solutions are required to mitigate such imbalances. This article evaluates 24 SoC equalisation circuits commonly seen in automotive applications. The analytic hierarchy process (AHP) technique to rank these equalisation circuits based on several choice criteria (energy efficiency, equalisation speed, implementation and control simplicity, hardware size, and total price) and have created a survey to collect design opinions from several battery balance specialists from around the world to better understand the relative importance of different variables. The bypass and passive approaches are easy to install and have minimal costs, but they have low energy efficiency.

Subramanian et al [25] examined the Peer-to-Peer (P2P) trade becomes familiar, which is primarily based on the completely decentralised process of power generation and consumption. Simultaneously, hybrid electric vehicles (HEV) have emerged as an important technology for achieving energy efficiency and environmental sustainability. Depending on the measurement, the BMS analyses the power and SoC and validates the well-being. Accurate SOC calculation is critical to ensuring the continuous operation of Li-ion batteries, which are commonly used in HEVs. A solid SOC prediction model is required to ensure accurate measurement of the vehicle's residual driving range and proper battery balancing. These methods combine a moving average prediction with a reduced electrochemical method capable of doing prediction with linearization error.

From the given researches, it is clear that [16] involved high computational time, [17] variation in the state information of the battery affected the estimation, [18] the clustering algorithm needs to be improved, [19] generalization ability needs to be improved, [20] the estimation results strongly depended on the initialization of parameters and [21] is not handle multiple sequences of input signals with different step lengths, in [22] the interior electrochemical variables are ignored, which is degrade the precision of state prediction as the battery ages or the load varies, in [23] the number of R-C components increases, so does the circuit's complexity and computing power, in [24] the bypass and passive techniques are simple to install and inexpensive, but they are inefficient in terms of energy use, in [25] these approaches combine moving average prediction with a simplified electrochemical method capable of predicting with linearization error. Hence, there is a need for a novel method for the accurate estimation of the SoC of Li-ion battery packs in electric vehicles.

3. EFFICIENT LI-ION BATTERY MANAGEMENT SYSTEM WITH LOSSLESS CHARGE BALANCER FOR RUL AND SOH PREDICTION

Electric vehicles use batteries to create their own mechanical power for transportation. As a result, it is critical to design a Battery Pack that can provide appropriate power to the motor for an extended period of time without diminishing its lifespan. To increases the lifespan of the batteries in EV by cell-balancing approaches and Prediction of RUL and SoH. In the existing cell-balancing approaches, energy loss during charge balancing operation and prediction errors happens in RUL and SoH. Hence a novel Efficient Li-ion Battery Management System with Lossless Charge Balancer for RUL and SoH Prediction is proposed, to reduce energy loss during charge balancing operation and avoid the prediction errors happens in RUL and SoH thereby increasing the lifespan of the Electric vehicle battery. In the existing energy management systems in lithium-ion battery packs of electric vehicles use various cell-balancing approaches which involve SoC estimation complexity due to energy loss during charge balancing operation because, in these approaches, each cell is connected to passive electronic devices for energy balancing which involve energy losses in the form of heat and create unavoidable instant charge imbalance. Thus, a novel Optimized Multi I/O Bi-LSTM has been proposed to estimate the SoC of the battery pack in the EV in which the MIMO-Bi-LSTM Unit receives the open circuit voltage (OCV), charging and discharging current (I_c and I_d) and temperature of each cell in the battery pack and estimates the SoC. This unit is capable of utilizing and keeping information from both sides i.e., every component of an input sequence has information from both the past and present based on the output values thus providing better SoC estimation. Additionally, an FFOA is utilized in this SoC estimation where it uses unique initialization and maximum generation approach to identify the population size thereby globally optimizing the different SoC values of each individual cell and estimating the SoC of the Batter Pack. With this approach, the SoC of individual cells, as well as the whole battery pack, are estimated with improved accuracy.

Moreover, to balance battery charge and improve cell life cycle, an Adaptive Matrix Gate Switch Balancer is introduced in which a matrix switch algorithm and Gate Turn-Off Thyristors are used for the charge balancing in each cell of the battery pack. The Adaptive Matrix Switch Algorithm compares the SoC values of each individual cell and selects the pairs of cells having a large difference in SoC values to assign first priority and then activates the relevant switches until they get charged equally. These steps are continued until every cell reaches the same SoC both during charging as well as discharging thereby avoiding charge imbalance. This Charge Balancer uses a having three terminals anode, cathode and a gate which switches the current in either direction in between cells aiding charging and discharging and the relevant switches are turned ON and OFF with the help of the Adaptive Matrix Switch Algorithm which applies a small positive and negative gate current accordingly. These switches have large switching frequencies and consume very less power for gate activation thereby reducing the energy loss during switching and improving the cell life cycle.

Prediction of remaining useful life (RUL) and SoH is a vital parameter for batteries to estimate remaining cycle life, which is defined as how many cycles from the present cycle the battery capacity will approach the failure threshold. But in the, existing methods take the real-time SoC data, aging factor, number of the present charge cycle and battery parameters and finally predict the RUL and SoH. These approaches involve prediction errors that cannot provide more reliable information for timely battery maintenance and replacement because they did not consider the variation of the EV motor’s efficiency that changes over a period of operation and the motor terminal resistance which also affects the cycle life of the battery. So the novel Optimized UK-ANFI Network is introduced for both RUL and SoH prediction in which a UK (Unscented Kalman) Filter is utilized to eliminate the non-linearity in the measured values of parameters such as SoC, aging factor, real-time motor efficiency and the motor terminal resistance using mean and covariance matching technique. The ANFI (Adaptive Neuro-Fuzzy Inference) Network receives these linearized data and predicts the RUL and SoH of the battery pack. Then a GWO (Grey Wolf Optimizer) is used to optimize these two output parameters from the ANFI unit thereby providing an enhanced life cycle prediction. With this combined and optimized prediction network, the prediction errors are minimized and more reliable battery information is attained with better life cycle prediction. Overall, with this proposed battery management and life cycle prediction approach, the estimation errors are minimized, and the life cycle of the battery and prediction accuracy is improved shown in figure 1.

Figure 1 despites the architecture of Efficient Li-ion Battery Management System with Lossless Charge Balancer for RUL and SoH Prediction of the proposed method. The battery has individual cell, each cell SoC is calculated by the MIMO-Bi-LSTM unit. The FFOA is used to optimize the individual SoC into the total SoC. Then the Adaptive Matrix Switch Algorithm compares the SoC values of each cell and activates the relevant switches until they get charged equally. The cells are connected with DGTO, it having three terminals anode, cathode and a gate which switches the current in either direction in between cells aiding charging and discharging and the relevant switches are turned ON and OFF with the help of the Adaptive Matrix Switch Algorithm. Furthermore, an Optimized UK-ANFI Network is introduced for both RUL and SoH prediction in which a UK (Unscented Kalman) Filter is utilized to eliminate the non-linearity in the measured values and the ANFI (Adaptive Neuro-Fuzzy Inference) Network receives these linearized data and predicts the RUL and SoH of the battery pack. Then a GWO (Grey Wolf Optimizer) is used to optimize these two output parameters from the ANFI unit thereby improving life cycle prediction.

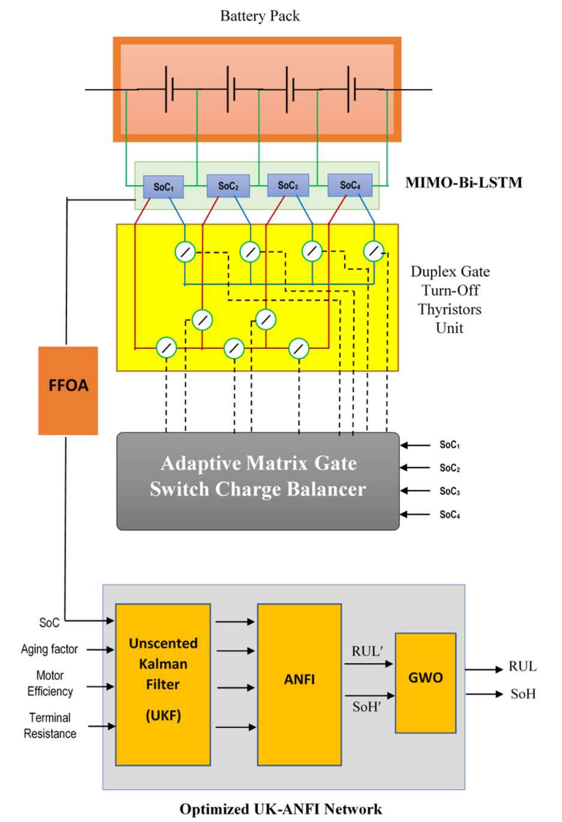

Figure 1. Architecture of Efficient Li-ion Battery Management System with Lossless Charge Balancer for RUL and SoH Prediction

3.1. Optimized Multi I/O Bi-LSTM

An Optimized Multi I/O Bi-LSTM has been proposed to estimate the SoC of the battery pack in the EV in which the MIMO-Bi-LSTM (Multi Input Multi Output-Bi directional Long Short-Term Memory) Unit receives the OCV, charging and discharging current (I_c and I_d) and temperature of each cell in the battery pack and estimates the SoC. Since some complication occurs in gated memory structure, LSTM solves the gradient disappearance or explosion problem that happens in regular RNNs and surpasses other recurrent architectures in dealing with sequential problems with long-term dependencies, however, that the LSTM structure can only leverage positive dependencies, and that some useful information will be filtered in the long-term gated memory chain. To address this issue, this research employs a bidirectional LSTM, which comprises of two LSTM layers facing opposite ways, two independent LSTM layers, one for forward sequence input and the other for reverse sequence input. This structure compensates for LSTM's lack of knowledge, better capture contextual long-term dependencies in sequence tasks, and enable more accurate predictions. This model's input data are multiple parameters such us OCV and charging and discharging current (I_c, I_d) and the input sequence $X_t = \{OCV_t, (I_c, I_d)_t, T_t\}$ is voltage, current and temperature with t as the time step, and the output sequence is SoC. The hidden layer of neuron node for the forward propagation of the model is given in equation 1 (26).

$$\vec{H}_t = LSTM\left(X_t, \vec{H}_{t-1}\right) \quad (1)$$

Where, $\vec{H}_t, \vec{H}_{t-1}$ is the hidden layer of neuron node for the forward propagation of the model

$$\overleftarrow{H}_t = LSTM\left(X_t, \overleftarrow{H}_{t-1}\right) \quad (2)$$

In equation (2), where $\overleftarrow{H}_t, \overleftarrow{H}_{t-1}$ is the hidden layer neuron nodes for the reverse propagation of the model. The forward and reverse implied state outputs of the Bi-LSTM are then connected and fed into the same fully connected layer, and the output implied layer state is considered as input using the fully connected layer. Its dimensionality reduction is calculated using the sigmoid function's activation function, and the final output is the projected charge state. The SoC estimation of the model output shows in equation (3).

$$SoC = W_m h_f + O_{rl} \quad (3)$$

Where, W_m denotes weight matrix, h_f is output of the fully connected layer, and O_{rl} is output regression layer. The flow diagram of BI- LSTM is shown in figure 2

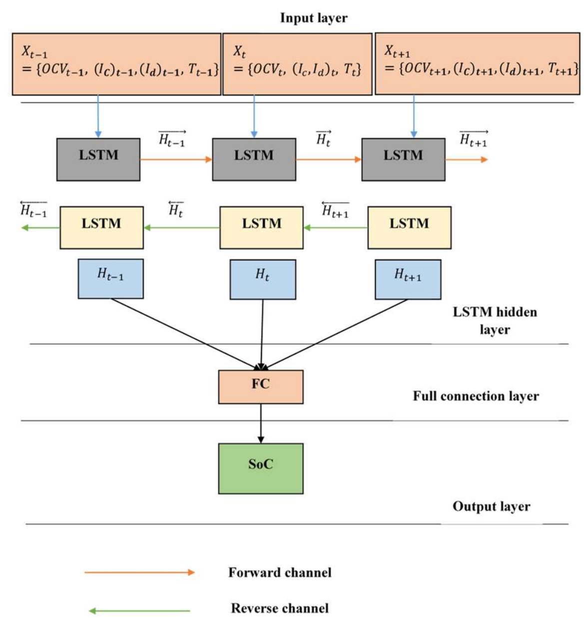

Figure 2. Structure of the Bi-LSTM

Figure 2 represents the structure of the Bi-LSTM of the proposed method. The four inputs such us OCV, charging and discharging current (I_c, I_d) and temperature of each cell in the battery pack are sent to the LSTM hidden layers, this LSTM receives the input parameters and processing by the reverse and forward channels in the LSTM hidden layer. Then it connected to the full connection layer, and finally the bidirectional LSTM is calculated the SoC of each cell. This unit is capable of utilizing and keeping information from both sides i.e., every component of an input sequence has information from both the past and present based on the output values thus providing better SoC estimation.

Additionally, an FFOA is utilized in this SoC estimation where it uses unique initialization and maximum generation approach to identify the population size thereby globally optimizing the different SoC values of each individual cell and estimating the SoC of the Battery Pack. It is used to solve optimization problems and is especially useful for ongoing optimization activities. The algorithm simulates the behaviour of fruit flies as they look for the best food sources in their surroundings.

Algorithm 1. FFOA (Fruit Fly Optimization Algorithm)

Input: The SoC of individual cell (SoC_1, SoC_2, SoC_3 and SoC_4) in the battery
Output: Total SoC
Step 1: Define an objective function that measures the fitness or quality of a certain SoC estimation. The objective function is based on estimation accuracy, divergence from actual SoC measurements, or other relevant factors.
Step 2: Create an initial population of potential SoC estimations that reflect various candidate solutions. These estimates are created at random within a defined range.
Step 3. In the FOA metaphor, each estimation candidate symbolises a fruit fly, and their behaviour is driven by the objective function. Fruit flies engage in a variety of behaviours, such as looking for food and associating with other fruit flies.
Step 4. The movement of fruit flies are depicted by modifying population calculations. Exploration and exploitation tactics can lead this trend in the pursuit for more accurate SoC estimations.
Step 5 Using the stated objective function, evaluate the fitness or quality of each estimation candidate. This evaluation determines how well each proposed SoC estimation corresponds with the desired estimation requirements.
Step 6. Apply a selection method to identify the most promising SoC estimation candidates based on their fitness scores. Higher fitness scores suggest estimates that are closer to the real SoC measurements.
Step 7. Repeat steps 4–6 for a set number of iterations or until a convergence requirement is reached. This iterative method allows the SoC estimating algorithm to continuously improve and converge towards a more accurate estimation.
Step 8. Once iterations, choose the estimation candidate with the best fitness score as the final SoC estimation.

The Fruit Fly Optimization Algorithm is well-known for its ability to efficiently explore the search space, find a balance between exploration and exploitation, and settle on solid solutions. It excels at continuous optimization issues with complicated and multimodal search spaces. With this approach, the SoC of individual cells, as well as the whole battery pack, are estimated with improved accuracy.

3.2. Adaptive Matrix Gate Switch Balancer

The Adaptive Matrix Gate Switch Balancer is introduced in which a matrix switch algorithm and Gate Turn-Off Thyristors are used for the charge balancing in each cell of the battery pack. This Charge Balancer uses a DGTO having three terminals anode, cathode and a gate which switches the current in either direction in between cells aiding charging and discharging and the relevant switches are turned ON and OFF with the help of the Adaptive Matrix Switch Algorithm which applies a small positive and negative gate current accordingly. The two gates are known as the main gate and the auxiliary gate. The main gate regulates the turn-on procedure, while the auxiliary gate controls the turn-off process. Are utilising the auxiliary gate, DGTOs can radically minimise turn-off losses, resulting in faster switching frequencies and lower power dissipation. DGTOs are often built to handle high voltages and currents, making them appropriate for high-power applications. DGTOs are distinguished by their ability to be turned off by applying a negative voltage pulse to the gate terminal. This feature distinguishes DGTOs from other thyristor devices, such as silicon-controlled rectifiers (SCRs), which can only be switched off by lowering the current flowing through them to zero. When a negative voltage pulse is supplied to the gate of a DGTO, the conductivity of the thyristor is reduced, causing the current to drop and eventually stop flowing. This is known as "gate turn-off." The DGTO's ability to be shut off quickly makes it excellent for applications needing fast and efficient switching, such as motor drives, traction systems, high-power inverters, and other industrial power electronics applications. These switches have large switching frequencies and consume very less power for gate activation thereby reducing the energy loss during switching and improving the cell life cycle. The DGTO shown in figure 3

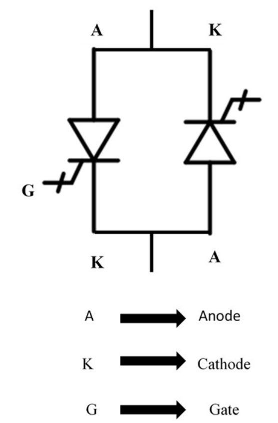

Figure 3. DGTO (Duplex Gate Turn-Off Thyristors)

Figure 3 represents the of the proposed method. The DGTO has three terminals anode, cathode, and a gate that switches the current in either direction between cells, assisting charging and discharging, and the relevant switches are turned ON and OFF with the help of the Adaptive Matrix Switch Algorithm, which applies a small positive and negative gate current accordingly. First it focused to balancing the maximum difference of SoC between two cells and balanced that two cells SoC then focused on other cells. This cycle was continuously repeated by DGTO by using adaptive matrix switch algorithm.

The Adaptive matrix switch algorithm is the computational approach or logic used to control and manage the switching of signals or data using a matrix switch in the context of networking or signal routing. The Adaptive Matrix Switch Algorithm compares the SoC values of each individual cell and selects the pairs of cells having a large difference in SoC values to assign first priority and then activates the relevant switches until they get charged equally. The matrix switch algorithm defines how signals are routed by the switch depending on particular criteria or rules. The following is the adaptive matrix switch algorithm.

Algorithm 2. The Adaptive Matrix Switch Algorithm

Input: Control the switches of DGTO for SoC balancing in each cell
Output: Balanced the SoC of each cell in the battery
Steps:

1. The size of the matrix is determined by the number of input and output ports necessary.
2. The gate signal governs the DGTO's turn-on and turn-off behaviour. A control circuit commonly employs a pulse generator or a microcontroller to generate the gate signal. Based on the required switching action, the algorithm determines the timing and duration of the gate pulses.
3. A negative voltage pulse applied to the gate initiates the turn-off process in DGTOs and sets the time and duration of the gate turn-off pulse.
4. DGTOs are susceptible to overcurrent and overvoltage circumstances, which is destroy the device or cause it to behave abnormally. In the event of an overcurrent or overvoltage incident, the control algorithm comprises protective mechanisms that monitor the current and voltage levels and initiate necessary responses, such as lowering the gate voltage or halting the gate pulses.
5. The control algorithm communicates with the gate drive circuitry to convert control signals into the voltage or current levels needed to efficiently operate the DGTO gates. Depending on the DGTO's exact gate drive needs, this is entail level shifting, isolation, and amplification approaches.
6. Feedback methods is used to monitor real device behaviour and compare it to desired switching characteristics. This enables the control algorithm to dynamically alter the gate signals to maintain optimal performance and respond to changing load conditions or system requirements.

To accomplishes efficient and reliable switching operations, the adaptive matrix switching algorithm is used for specific device features such as gate capacitance, gate charge, and switch turn-on and turn-off characteristics. These steps are continued until every cell reaches the same SoC both during charging as well as discharging thereby avoiding charge imbalance. The flow diagram of Adaptive Matrix Gate Switch Balancer is shown in figure 4.

Figure 4 represents flow chart of adaptive matrix gate switch balancer of the proposed method. The Adaptive Matrix Gate Switch Balancer is introduced, which uses a matrix switch algorithm and Gate Turn-Off Thyristors for charge balancing in each cell of the battery pack. The Adaptive Matrix Switch Algorithm examines the SoC values of each individual cell and picks pairings of cells with a big difference in SoC values to assign first priority, and then activates the relevant switches until they are charged equally. These procedures are repeated until every cell reaches the same SoC when charging and draining, avoiding charge imbalance. This Charge Balancer employs a DGTO with three terminals anode, cathode, and a gate that switches the current in either direction between cells, assisting charging and discharging, and the relevant switches are turned ON and OFF with the assistance of the Adaptive Matrix Switch Algorithm, which applies a small positive and negative gate current accordingly.

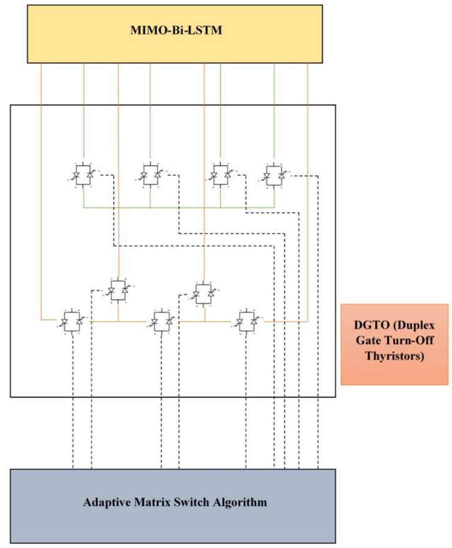

Figure 4. Flow chart of adaptive matrix gate switch balancer

These switches have high switching frequencies and use relatively little power for gate activation, decreasing energy loss and enhancing cell life cycle. In following section discussed about the prediction of RUL and SoH of the battery efficiently.

3.3. Optimized UK-ANFI Network

An Optimized UK-ANFI Network is introduced for both RUL and SoH prediction in which a Filter is used to eliminate the non-linearity in the measured values of parameters such as SoC, aging factor, real-time motor efficiency and the motor terminal resistance using mean and covariance matching technique. The UK Filter eliminate the non-linearity by a mathematical model, that represents the system dynamics and how the measured values relate to the parameters of interest is established. The model represents the non-linear correlations between the parameters (SoC, aging factor, real-time motor efficiency, motor terminal resistance) and the measured values in the scenario. Then the state vector contains the estimated parameters of interest, such as SoC, aging factor, motor efficiency, and motor terminal resistance. The measured values of these parameters are included in the measurement vector. The UKF predict the present state (parameters) based on the prior state and the system dynamics model. It propagates the mean and covariance of the state through the non-linear model to estimate the projected state. The UKF employs the unscented transform to choose a collection of sigma points (representative points) that encapsulate the mean and covariance of the anticipated state. These sigma points are then fed into the non-linear measurement model to generate anticipated measurements. The UKF estimates the Kalman gain by comparing expected and actual measurements. The Kalman gain adjusts the mean and covariance of the state estimate by combining the anticipated state estimate with the actual data. Using the Kalman gain, the UKF updates the state estimate. The revised state estimate becomes the estimated values of the parameters (SoC, aging factor, motor efficiency, motor terminal resistance). The method is then repeated for consecutive measurements. The UKF provides an effective method for estimating the parameters of interest by iteratively propagating the mean and covariance of the state through non-linear models and adding actual data. The SoC of each cell (SoC_1, SoC_2, SoC_3, SoC_4) is converted into total SoC by FFOA (Fruit Fly Optimization Algorithm) and the total SoC is sent to the (Unscented Kalman) Filter. Then the parameters such as SoC, aging factor, motor efficiency, motor terminal resistance are entered in the ANFI Network.

The ANFI Network receives these linearized data from UK Filter and these data are first analysed under fuzzy conditions in ANFIS modelling. The data is then trained using fuzzy rules, and the error is decreased using IF-THEN and membership functions. The Sugeno type of fuzzy inference system is built from cluster information and employs a small number of rules to accurately represent data behaviour. The rules are self-divided in terms of the fuzzy properties of each data cluster. To train the ANFIS model, derivative-based methods such as backpropagation make use of each node with differentiable functions. To update the parameters of the ANFI network, use the training dataset. The training method seeks to minimise the difference between the projected RUL and SoH values and the ground truth values in the training dataset. Using the testing dataset, evaluate the performance of the trained ANFI network. To analyse the accuracy of the predictions, compute relevant performance metrics such as mean squared error or root mean squared error. Based on the evaluation results, adjust the ANFI network parameters as needed. Input new battery operating conditions and metrics into the trained ANFI network. The ANFI network uses fuzzy inference based on language rules and membership functions to predicts the RUL and SoH of the battery pack. The GWO is used to optimize these RUL and SoH output parameters from the ANFI unit. The following is the Grey Wolf Optimizer algorithm.

Algorithm 3. Grey Wolf Optimizer

Input: RUL and SoH from ANFI unit
Output: Optimized RUL and SoH values
Steps:

1. The objective function should examine the accuracy and dependability of the forecasts, taking into account the actual RUL and SoH values as well as the predictions provided by the ANFI unit.
2. Identify the two output parameters, RUL and SoH, that must be optimized to improve life cycle prediction and the define the search space boundries for these parameters, describing their permitted ranges.
3. Set the GWO algorithm parameters, such as population size, maximum number of iterations, and search space boundaries for RUL and SoH. Randomly locate the grey wolves (solutions) inside the defined search space and calculate the fitness value for each grey wolf based on the goal function as predicted by the ANFI unit.
4. Iterate over a number of generations or until a termination condition is met. Update the grey wolves' positions based on their fitness scores, as well as the positions of the alpha, beta, and delta wolves (best solutions identified so far). Utilise grey wolf hunting behaviour to alter the positions of the grey wolves while exploring and utilising the search space
5. Using the ANFI unit's predictions, update the fitness values for the grey wolves' new placements. Update the placements of the alpha, beta, and delta wolves on a regular basis based on the greatest fitness values obtained.
6. Decide a termination condition, such as completing the maximum number of iterations or getting a desirable fitness value. Return to step 4 and resume the optimisation procedure if the termination condition is not fulfilled.
7. When the optimization procedure is finished, the position of the alpha wolf represents the optimised values for RUL and SoH from the ANFI unit. These optimized parameter values were used to improve life cycle prediction, resulting in increased accuracy and reliability of RUL and SoH estimations.

Through using the GWO algorithm to optimize the RUL and SoH output parameters from the ANFI unit, and achieve more accurate and reliable life cycle predictions for the system. The GWO's exploration and exploitation capabilities aid in the discovery of optimal RUL and SoH values, thereby providing an enhanced life cycle prediction. With this combined and optimized prediction network, the prediction errors are minimized and more reliable battery information is attained with better life cycle prediction.

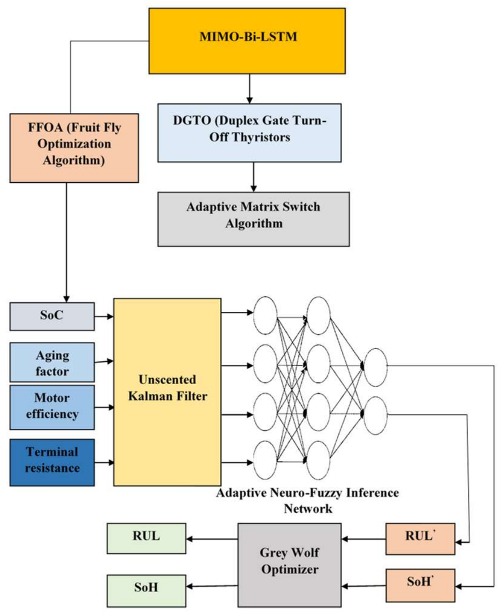

Figure 5. Flow chart of optimized UK-ANFI Network

Figure 5 represents the flow chart of optimized UK-ANFI Network in the proposed method. A UK Filter is used to eliminate non-linearity in measured values of parameters such as SoC, ageing factor, real-time motor efficiency, and motor terminal resistance using mean and covariance matching technique in the optimised UK-ANFI Network for both RUL and SoH prediction. The ANFI Network gets this linearized data and forecasts the battery pack's RUL and SoH. Then, a GWO is utilised to optimise these two output parameters from the ANFI unit, delivering an improved life cycle prediction. With this merged and optimised prediction network, prediction errors are reduced and more trustworthy battery information is obtained with superior life cycle prediction.

Overall, the proposed MIMO-Bi-LSTM (Multi Input Multi Output-Bi weDirectional Long Short-Term Memory) Unit receives the OCV, charging and discharging current (I_c and I_d) and temperature of each cell in the battery pack and estimates the SoC and the FFOA is used to calculate the different SoC values of each individual cell and estimating the SoC with high accuracy. In the charge balancing in each cell of the battery pack, the Adaptive Matrix Switch Algorithm compares the SoC values of each individual cell and selects the pairs of cells having a large difference in SoC values and avoiding charge imbalance. The DGTO have large switching frequencies and consume very less power for gate activation thereby reducing the energy loss during switching and improving the cell life cycle. In the prediction of RUL and SoH of the battery pack, UK Filter is used to eliminate the non-linearity in the measured values. ANFI Network receives these linearized data and predicts the RUL and SoH of the battery pack. Then a GWO is used to optimize these two output parameters from the ANFI unit thereby providing an enhanced life cycle prediction. Thereby, the existing techniques drawbacks are overcome by this proposed method. In following section, 4 discussed about performance and comparison of proposed method.

4. RESULT AND DISCUSSION

The results obtained from the proposed model have been provided in this section. The results showed that the proposed model minimized the estimation errors, and improved the life cycle of the battery, and the prediction accuracy of the proposed approach is also proved by comparing it with other existing approaches.

4.1. Experimental setup

OS	:	Windows 10 Professional 64 bit
RAM	:	8GB
Processer	:	intel(R) Core (TM) i3-4130 CPU @ 3.40GHz 3.40 GHz
Tool	:	Matlab

4.2. Simulation result

This section described the simulation result of the proposed method. The circuit diagram of the balancing algorithm, and thyristor filter are shown in figure 6 and figure 7.

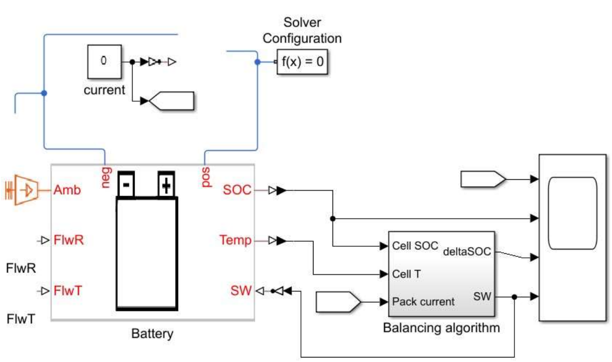

Figure 6. Simulated view of Balancing algorithm of the proposed method

Figure 6 represents the Balancing algorithm of the proposed method. The energy pass through the battery, the cell SoC, temperature of cell balance by adaptive matrix switch algorithm. This adaptive matrix switch algorithm control the DGTO switches and tranfering the power in each cell of the battery, the first prioritygiven to large difference charge values in cell and it balanced, then check to the other large difference charge in the cell. The total SoC of battery pack is calculated by FFOA and the total SoC sent to the Unscented Kalman Filter.

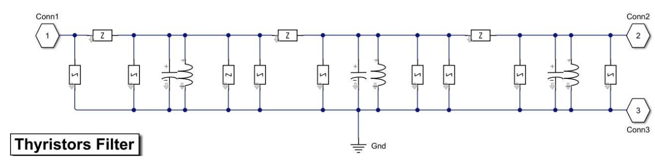

Figure 7. Simulated view of thyristors filter of the proposed method

Figure 7 represents the thyristor filter of the proposed method. The first step is to measure the current or voltage waveform that has to be filtered. The signal is acquired using sensors or transducers. Based on the desired filtering characteristics, a reference waveform is constructed. The measured and reference waveforms are compared to discover the differences or errors between them. A microcontroller or a digital signal processor is often used for this. Control signals are generated to trigger the thyristors based on the comparison results. Control signals dictate whether the thyristors conduct or inhibit current flow.Control signals are created and supplied to thyristors that are coupled in a specified configuration (such as a bridge or matrix). To selectively enable or stop current flow, the thyristors are switched on and off based on the control signals. Thyristors can alter the current or voltage waveform when they turn on and off by introducing compensatory currents or voltages. This compensatory effect cancels out the unwanted harmonics and noise in the original waveform, resulting in a cleaner output waveform. The entire process is constantly watched, and adjustments are made as needed to keep the optimum filtering performance. The feedback loop guarantees that the filter responds to changes in the input waveform and compensates accurately.

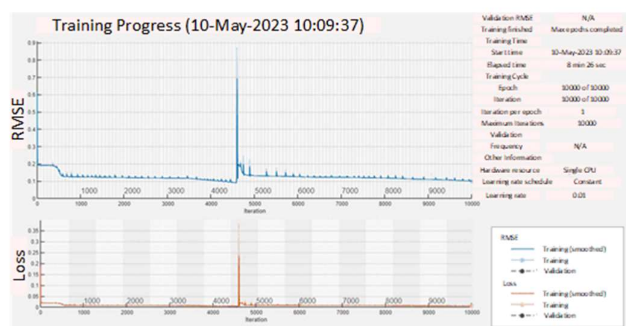

Figure 8. RMSE and loss prediction of the proposed method

Figure 8 represents the RMSE and loss prediction of the proposed method. During simulation, set up the UKF's initial state estimation, covariance matrices, and other relevant parameters. Apply the UKF algorithm to the measurement data to estimate the system state at each time step. The UKF incorporates nonlinear system dynamics and measurement equations to iteratively update the state estimation and covariance matrices. When running the UKF, compare the estimated state values to the genuine state values at each time step. To determine the RMSE value, compute the squared differences between the estimated and true states, total them over all time steps, divide by the total number of time steps, and take the square root.

4.3. Performance metrics of the proposed model

The performance metrics of the proposed model in the battery management system and high prediction of RUL and SoH of the proposed approach based on achieved outcome were explained in detail in this section.

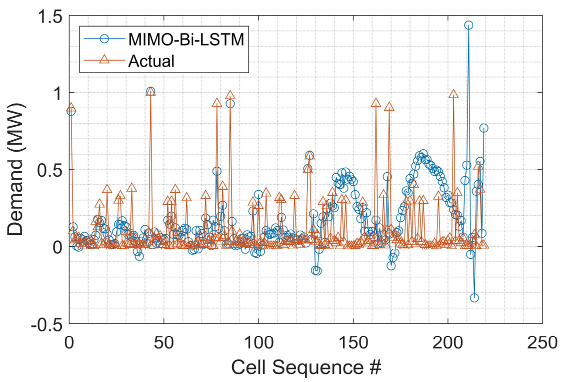

Figure 9. Performance of demand in the proposed model

Figure 9 illustrates the performances of the demand of the proposed model. When the number of cell sequence is 210 it achieves the maximum demand of 1.42 MW and while the number of cell sequence is 215, it achieves the minimum cell sequence of -0.32 MW. The MIMO-Bi-LSTM, input sequence has information from both the past and present based on the output values thus providing better SoC estimation than actual SoC value.

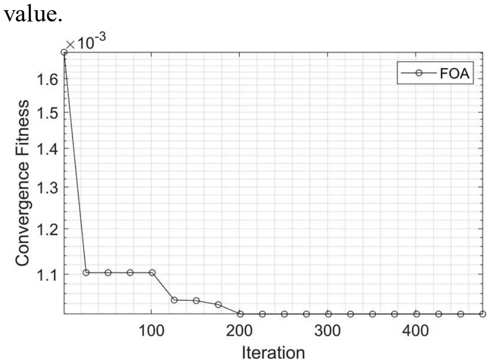

Figure 10. Performance of convergence fitness in the proposed model

Figure 10 illustrates the performances of the convergence fitness of the proposed model. When the number of iteration is 0 it achieves the maximum convergence fitness of 1.7 x 10^{-3} and while the number of iteration is 200, it achieves the minimum convergence fitness of 1 x 10^{-3} and it constant upto 500 iteration. The FFOA is utilized in this SoC estimation where it uses unique initialization and maximum generation approach to optimize the convergence fitness once every iteration.

Figure 11 illustrates the performances of the first state validation of the proposed model. When the time is 0 second it achieves the maximum first state validation of 2 and it gradually decreasing while the time is 3 seconds, it achieves the minimum first state validation is -2 for true value. The Unscented Kalman Filter, filtered the non-linearity values in the parameter, thus the curve is not more fluctuated from the true value.

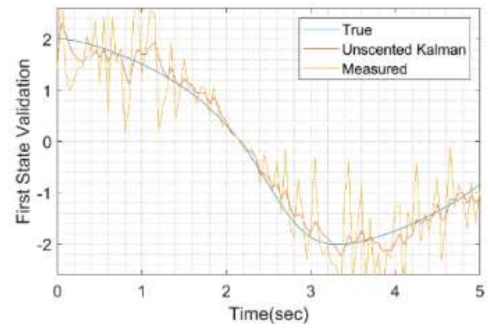

Figure 11. Performance of first state validation in the proposed model

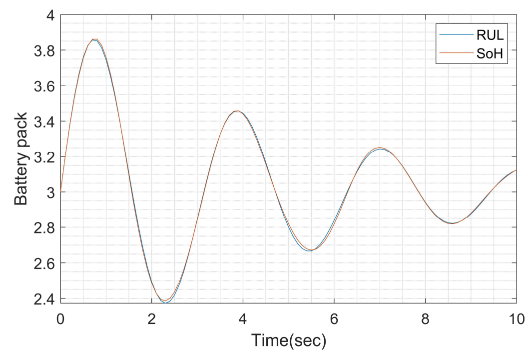

Figure 12. Performance of RUL and SOH in the proposed model

Figure 12 illustrates the performances of the RUL and SOH of the proposed model. When the time is 0.6 second, the RUL achieves the maximum battery pack of 3.82 and while the time is 2.1 seconds, it achieves the minimum battery pack of 2.4 and the time is 0.6 seconds SOH achieves the maximum battery pack of 3.82 and while the time is 2.1 seconds, it achieves the minimum battery pack of 2.4. The adaptive neuro-fuzzy inference network receives linearized data from UK Filter and predicts the RUL and SoH of the battery pack.

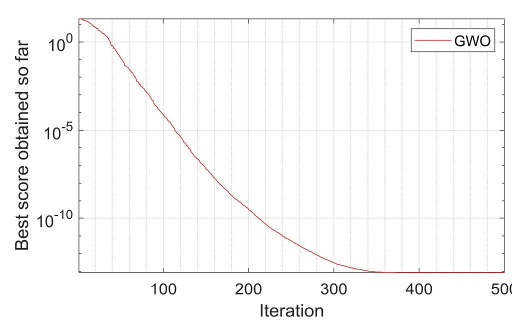

Figure 13. Performance of best score in the proposed model

Figure 13 illustrates the performances of the magnitude of the proposed model. When the number of iteration is 0 it achieves the maximum best score of $10^{1.2}$ and while the number of iteration is 360 it achieves the minimum best score of 10^{-15} and it continuous constant upto 500 iteration. The grey wolf optimizer is used to optimize the two output parameters from the ANFI unit thereby the best score obtained is gradually reduced once every iteration.

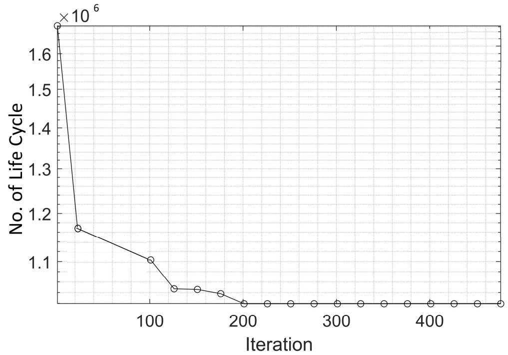

Figure 14. Performance of number of life cycle in the proposed model

Figure 14 illustrates the performances of the number of life cycle of the proposed model. When the number of iteration is 0 it achieves the maximum number of life cycle of 1.7 x 10^6 and while the number of iteration is 200 it achieves the minimum number of life cycle of 1 x 10^6 and it continuous constantly upto 500 iteration. The number of life cycle of the battery is optimized by grey wolf optimizer by optimizing ANFI outputs, the number of lifecycles decreased once every iteration.

The comparison of the performance of the proposed approach with other existing approaches is discussed in the following section 4.4.

3.4. Comparison of Proposed Model with Previous Models

This section highlights the proposed method's performance by comparing it to the outcomes of existing approaches and showing their results based on various metrics.

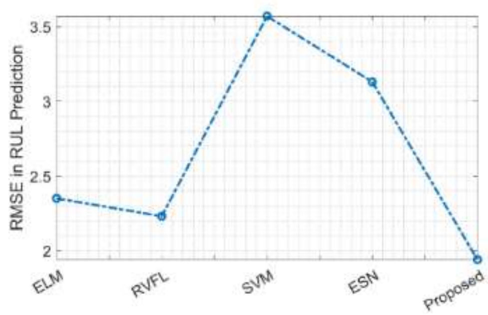

Figure 15. Comparison of RMSE in RUL prediction in the proposed model

Figure 15 depicts the comparison of the RMSE in RUL prediction of the proposed model with other existing approaches. The RMSE of the proposed approach is compared with existing techniques such as ELM, RVFL, SVM, and ESN [27]. The RMSE of the proposed model obtains the value of 1.8% whereas the RMSE of ELM, RVFL, SVM, and ESN are 2.4%, 2.2%, 3.6%, and 3.12% respectively. The RMSE in RUL prediction of the proposed model is low whereas the RMSE in RUL prediction of SVM is high.

Figure 16 depicts the comparison of the RMSE in SoH prediction of the proposed model with other existing approaches. The RMSE of the proposed approach is compared with existing techniques such as ELM, RVFL, SVM, and ESN [27].

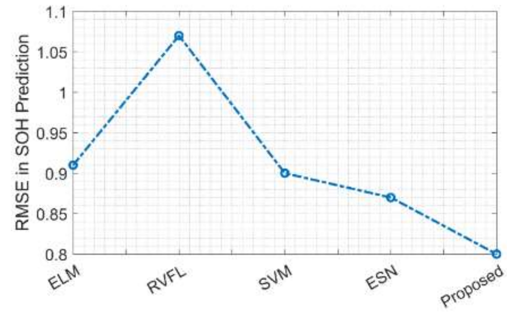

Figure 16. Comparison of RMSE in SoH prediction in the proposed model

The RMSE of the proposed model obtains the value of 0.8% whereas the RMSE of ELM, RVFL, SVM, and ESN are 0.91%, 1.06%, 0.9% and 0.87% respectively. The RMSE in SoH prediction of the proposed model is low whereas the RMSE in SoH prediction of RVFL is high.

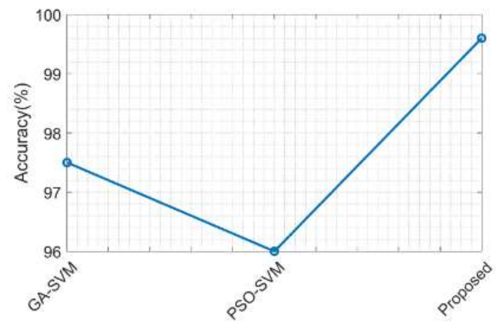

Figure 17. Comparison of Accuracy in the proposed model

Figure 17 depicts the comparison of the accuracy of the proposed model with other existing approaches. The accuracy of the proposed approach is compared with existing techniques such as GA-SVM and PSO-SVM [28]. The accuracy of the proposed model obtains the value of 99.6% whereas the accuracy of GA-SVM and PSO-SVM are 97.8%, and 96% respectively. The accuracy of the proposed model is high whereas the accuracy of PSO-SVM is low.

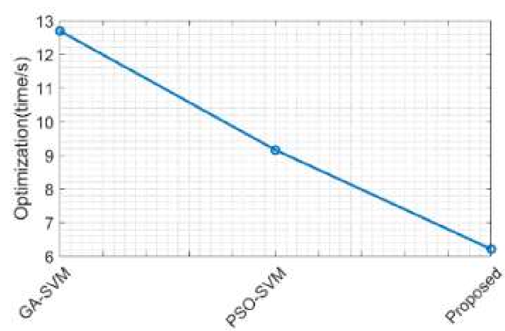

Figure 18. Comparison of optimization time in the proposed model

Figure 18 depicts the comparison of the optimization time of the proposed model with other existing approaches. The optimization time of the proposed approach is compared with existing techniques such as GA-SVM and PSO-SVM [28]. The optimization time of the proposed model obtains the value of 6.1 seconds whereas the optimization time of GA-SVM and

PSO-SVM are 12.8 seconds, and 9 seconds respectively. The optimization time of the proposed model is low whereas the optimization time of GA-SVM is high.

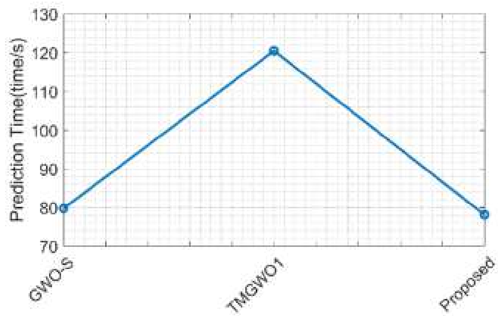

Figure 19. Comparison of prediction time in the proposed model

Figure 19 depicts the comparison of the prediction time of the proposed model with other existing approaches. The prediction time of the proposed approach is compared with existing techniques such as GWO-S and TMGWO1 [29]. The prediction time of the proposed model obtains the value of 76 seconds whereas the prediction time of GWO-S and TMGWO1 are 80 seconds, and 120 seconds respectively. The prediction time of the proposed model is low whereas the prediction time of TMGWO1 is high.

Overall, the proposed method has a good result compared to the existing method, the RMSE in RUL prediction and the RMSE in SoH prediction value is 1.8% and 0.8% compared to exiting method, the proposed is high. The accuracy of the proposed method is 99.6 % and the optimization time is 6.1 seconds. The prediction time of RUL and SoH is 76 seconds, when compared to existing method, the proposed method obtains good result. As a result, the battery management system of the proposed method gives low RMSE in RUL and SoH prediction, high accuracy, low optimization time, and low prediction time.

5. CONCLUSION

Electric vehicles employ a Battery Maintenance System (BMS) to protect the battery pack by combining additional cells and dealing with the voltage and current demands of EV motors. The estimation of the SoC in battery pack by MIMO-Bi-LSTM Unit and the FFOA is utilized in which the SoC of individual cells, as well as the whole battery pack, are estimated the SoC with high accuracy of 99.6%. Moreover, the Adaptive Matrix Switch Algorithm compares the SoC values of each individual cell and selects the pairs of cells having a large difference in SoC values thereby avoiding charge imbalance. The DGTO switches have large switching frequencies and consume very less power for gate activation thereby reducing the energy loss during switching and improving the cell life cycle and low optimization time of 6.1 seconds. Furthermore, the UK Filter is utilized to eliminate the non-linearity in the measured values of parameters and the ANFI Network receives these linearized data and predicts the RUL and SoH with low RMSE of 1.8% and 0.8%, then the GWO is used to optimize these two output parameters from the ANFI unit and reduced the prediction time of 76 seconds. Overall, the cell charge balancing and the prediction of RUL and SoH also obtained good results compared to the existing method. Thus, the proposed battery management system of electric vehicles, successfully estimated the better SoC value, prediction of remaining useful life and SoH of batteries by eliminating the prediction errors, problems in the charge balancing strategies.

REFERENCES

[1] Hu, G., Huang, P., Bai, Z., Wang, Q and Qi, K. (2021). Comprehensively analysis the failure evolution and safety evaluation of automotive lithium ion battery. ETransportation, 10: 100140. https://doi.org/10.1016/j.etran.2021.100140

[2] Houache, M.S., Yim, C.H., Karkar, Z and Abu-Lebdeh, Y. (2022). On the Current and Future Outlook of Battery Chemistries for Electric Vehicles—Mini Review. Batteries, 8(7): 70. https://doi.org/10.3390/batteries8070070

[3] Li, C., Cui, N., Chang, L., Cui, Z., Yuan, H and Zhang, C. (2022). Effect of parallel connection topology on air-cooled lithium-ion battery module: Inconsistency analysis and comprehensive evaluation. Applied Energy, 313: 118758. https://doi.org/10.1016/j.apenergy.2022.118758

[4] Bobobee, E.D., Wang, S., Zou, C., Takyi-Aninakwa, P., Zhou, H and Appiah, E. (2023). State of charge estimation of ternary lithium-ion batteries at variable ambient temperatures. International Journal of Electrochemical Science, 18(4): 100062. https://doi.org/10.1016/j.ijoes.2023.100062

[5] Tang, X., Gao, F., Liu, K., Liu, Q and Foley, A.M. (2021). A balancing current ratio based state-of-health estimation solution for lithium-ion battery pack. IEEE Transactions on Industrial Electronics, 69(8): 8055-8065. https://doi.org/10.1109/TIE.2021.3108715

[6] Takyi-Aninakwa, P., Wang, S., Zhang, H., Appiah, E., Bobobee, E.D and Fernandez, C. (2022). A strong tracking adaptive fading-extended Kalman filter for the state of charge estimation of lithium-ion batteries. International Journal of Energy Research, 46(12): 16427-16444. https://doi.org/10.1002/er.8307

[7] Guo, R and Shen, W. (2022). A data-model fusion method for online state of power estimation of lithium-ion batteries at high discharge rate in electric vehicles. Energy, 254: 124270. https://doi.org/10.1016/j.energy.2022.124270

[8] Chen, Y., Yang, X., Luo, D and Wen, R. (2021). Remaining available energy prediction for lithium-ion batteries considering electrothermal effect and energy conversion efficiency. Journal of Energy Storage, 40: 102728. https://doi.org/10.1016/j.est.2021.102728

[9] Zhang, S and Zhang, X. (2021). Joint estimation method for maximum available energy and state-of-energy of lithium-ion battery under various temperatures. Journal of Power Sources, 506: 230132. https://doi.org/10.1016/j.jpowsour.2021.230132

[10] Zheng, Y., Cui, Y., Han, X and Ouyang, M. (2021). A capacity prediction framework for lithium-ion batteries using fusion prediction of empirical model and data-driven method. Energy, 237: 121556. https://doi.org/10.1016/j.energy.2021.121556

[11] Manoharan, A., Begam, K.M., Aparow, V.R and Sooriamoorthy, D. (2022). Artificial neural networks, gradient boosting and support vector machines for electric vehicle battery state estimation: A review. Journal of Energy Storage, 55: 105384. https://doi.org/10.1016/j.est.2022.105384

[12] Yin, H., Ma, S., Li, H., Wen, G., Santhanagopalan, S and Zhang, C. (2021). Modeling strategy for progressive failure prediction in lithium-ion batteries under mechanical abuse. ETransportation, 7: 100098. https://doi.org/10.1016/j.etran.2020.100098

[13] He, X., Sun, B., Zhang, W., Fan, X., Su, X and Ruan, H. (2022). Multi-time scale variable-order equivalent circuit model for virtual battery considering initial polarization condition of lithium-ion battery. Energy, 244: 123084. https://doi.org/10.1016/j.energy.2021.123084

[14] Hong, J., Wang, Z., Chen, W., Wang, L., Lin, P and Qu, C. (2021). Online accurate state of health estimation for battery systems on real-world electric vehicles with variable driving conditions considered. Journal of Cleaner Production, 294: 125814. https://doi.org/10.1016/j.jclepro.2021.125814

[15] Han, T., Wang, Z., Meng, H. (2022). End-to-end capacity estimation of Lithium-ion batteries with an enhanced long short-term memory network considering domain adaptation. J. Power Sources, 520: 230823. https://doi.org/10.1016/j.jpowsour.2021.230823

[16] Park, K., Choi, Y., Choi, W.J., Ryu, H.Y and Kim, H. (2020). LSTM-based battery remaining useful life prediction with multi-channel charging profiles. IEEE Access, 8: 20786-20798. https://doi.org/10.1109/ACCESS.2020.2968939

[17] Wang, S., Fan, Y., Jin, S., Takyi-Aninakwa, P and Fernandez, C. (2023). Improved anti-noise adaptive long short-term memory neural network modeling for the robust remaining useful life prediction of lithium-ion batteries. Reliability Engineering & System Safety, 230: 108920. https://doi.org/10.1016/j.ress.2022.108920

[18] Tian, H., Li, A and Li, X. (2021). SOC estimation of lithium-ion batteries for electric vehicles based on multimode ensemble SVR. Journal of Power Electronics, 21(9): 1365-1373. https://doi.org/10.1007/s43236-021-00279-9

[19] Cui, Z., Kang, L., Li, L., Wang, L and Wang, K. (2022). A hybrid neural network model with improved input for state of charge estimation of lithium-ion battery at low temperatures. Renewable Energy, 198: 1328-1340. https://doi.org/10.1016/j.renene.2022.08.123

[20] Wang, Z., Feng, G., Liu, X., Gu, F and Ball, A. (2022). A novel method of parameter identification and state of charge estimation for lithium-ion battery energy storage system. Journal of Energy Storage, 49: 104124. https://doi.org/10.1016/j.est.2022.104124

[21] Yang, K., Tang, Y., Zhang, S and Zhang, Z. (2022). A deep learning approach to state of charge estimation of lithium-ion batteries based on dual-stage attention mechanism. Energy, 244: 123233. https://doi.org/10.1016/j.energy.2022.123233

[22] Gao, Y., Zhu, C., Zhang, X and Guo, B. (2021). Implementation and evaluation of a practical electrochemical-thermal model of lithium-ion batteries for EV battery management system. Energy, 221: 119688. https://doi.org/10.1016/j.energy.2020.119688

[23] Sagar, B.S., Santoshkumar Hampannavar, and Bansilal Bairwa. (2022). Applications of Battery Management System (BMS) in Sustainable Transportation: A Comprehensive Approach from Battery Modeling to Battery Integration to the Power Grid. World Electric Vehicle Journal, 13(5): 80. https://doi.org/10.3390/wevj13050080

[24] de Alcântara Dias, B.M., da Silva, C.T., Araújo, R.E., de Castro, R., Pellini, E.L., Pinto, C and Laganá, A.A.M. (2022). An Analytic Hierarchy Process for Selecting Battery Equalization Methods. Energies, 15(7): 2439. https://doi.org/10.3390/en15072439

[25] Annamalai, S., Mangaiyarkarasi, S.P., Rani, M.S., Ashokkumar, V., Gupta, D and Rodrigues, J.J. (2022). Design of peer-to-peer energy trading in transactive energy management for charge estimation of lithium-ion battery on hybrid electric vehicles. Electric Power Systems Research, 207: 107845. https://doi.org/10.1016/j.epsr.2022.107845

[26] Yang, B., Wang, Y and Zhan, Y. (2022). Lithium Battery State-of-Charge Estimation Based on a Bayesian Optimization Bidirectional Long Short-Term Memory Neural Network. Energies, 15(13): 4670. https://doi.org/10.3390/en15134670

[27] Gou, B., Xu, Y and Feng, X. State-of-health estimation and remaining-useful-life prediction for lithium-ion battery using a hybrid data-driven method. IEEE Transactions on Vehicular Technology, 69(10): 10854-10867, 2020. https://doi.org/10.1109/TVT.2020.3014932

[28] Li, B., Luo, C and Wang, Z. (2020). Application of GWO-SVM algorithm in arc detection of pantograph. IEEE Access, 8: 173865-173873. https://doi.org/10.1109/ACCESS.2020.3025714

[29] Abdel-Basset, M., El-Shahat, D., El-Henawy, I., De Albuquerque, V.H.C and Mirjalili, S. (2020). A new fusion of grey wolf optimizer algorithm with a two-phase mutation for feature selection. Expert Systems with Applications, 139: 112824. https://doi.org/10.1016/j.eswa.2019.112824