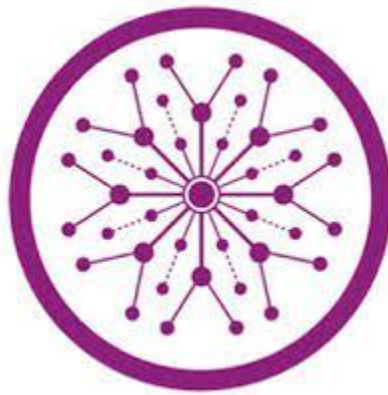


FORECASTING OF BATTERY LIFESPAN AND MONITORING SYSTEM USING ARTIFICIAL INTELLIGENCE (AI)



B.Sc. ELECTRICAL ENGINEERING

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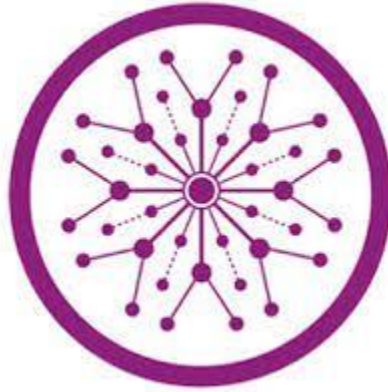
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FORECASTING OF BATTERY LIFESPAN AND MONITORING SYSTEM USING ARTIFICIAL INTELLIGENCE (AI)

A thesis submitted in partial fulfillment of the requirements for the
Degree of Bachelor of Science in
Electrical Engineering

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DECLARATION

This thesis is a presentation of my original research work. Wherever contributions of others are involved, every effort is made to indicate this clearly, with due reference to the literature, and acknowledgment of collaborative research and discussions. I also declare that this work is the result of my own investigations, except where identified by references, and free from plagiarism of the work of others.

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Thank you to all those who have supported me throughout this journey

Thank you,

Adnan Amin

M Tayyab Mushtaq

DEDICATION

We would like to dedicate this thesis to our beloved family, teachers, and friends.

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LIST OF ABBREVIATIONS

AI	Artificial intelligence
ANN	Artificial neural network
EV	Electric vehicle
LSTM	Long short-term memory
NASA	National Aeronautics and Space Administration
MAE	Mean Absolute Error
MC-LSTM	Multi-channel LSTM
MSE	Mean Squared Error
RNN	Recurrent neural network
RMSE	Root-mean-squared error
RUL	Remaining useful life
SOC	State of charge
SOH	State of health
UART	Universal Asynchronous Receiver-Transmitter
UPS	Uninterruptible Power Supply

ABSTRACT

Batteries are typically used in a variety of high-power uses, such as grid stations, uninterruptible power supply (UPS), and electric and hybrid vehicles (HEVs), where an accurate estimation and monitoring system for batteries is crucial to their safe and dependable functioning. By using the most recent Artificial Intelligence (AI) approach, the forecasting of Battery Lifespan and Monitoring system offers the battery monitoring health parameters, such as State of Charge (SOC), State of Health (SOH), temperature, current, and voltage, between all stakeholders, including manufacturers, market dealers, users, etc. When these features are accessed, corrective action can be taken to extend battery life.

A Long Short-Term Memory (LSTM) neural network is used in the project to assess events that occur over time. The method is suitable for forecasting battery SOH over time because it can capture long-term dependencies and retain previous inputs over a longer span of time. The ANN can forecast a non-measurable factor like the SOH of the battery based on battery-measured data like capacity, temperature, current, and voltage. This framework involves collecting data from a variety of battery-attached sensors, including temperature, current, and voltage, along with sending these values to the Arduino controller, which then displays the State of Charge (SOC) as well as battery condition parameters temperature, current, and the voltage on LCD. Here, a microcontroller is serially connected to the ESP module in order to make a dataset file on the system. On the basis of the information collected from the sensors, the LSTM model is then utilized to estimate the SOH of the battery in real-time. Thus comparing the estimated SOH values with the observed SOH values acquired from the test set, the LSTM model's accuracy is evaluated. Overall, the LSTM methodology is a promising method that can increase the performance and dependability of systems driven by batteries by forecasting the battery's lifespan in real-time. As a result, battery failures can be minimized, maintenance expenses can be decreased, and battery life can be prolonged.

CHAPTER 1

INTRODUCTION

1.1 Introduction

Any energy-supplying system must have storage facilities, especially batteries. Due to their advantageous cost, cycle life, and energy density compared to other energy storage technologies, batteries are utilized in various applications [1]. They were primarily used in electronic products and small electronics from the time of their exploitation in the 1990s until the start of the 2010s, such as laptops and cell phones, but with advancements in technology and price reductions, they have discovered a wide range of new uses, especially in electric automobiles and stationary stored energy. The significance of lithium-ion batteries in both the energy and transportation industries will continue to grow for many years as advancement in technology grows and pressure from politicians to minimize the usage of fossil fuels grows. Therefore, research on batteries receives significant effort and funding. It has become incredibly difficult for manufacturers and market dealers to provide service solutions to end customers due to exponential development in the annual production of batteries.

In recent years, there has been a conflict between the fast rising demand for electricity and the need to slow battery aging to improve system performance. Batteries serve as essential parts of electrical devices. Batteries are widely employed in a range of applications, such as electric-hybrid vehicles, electric automobiles (EVs), and electrical appliances because of their numerous benefits of sustainable characteristics, high density of power, minimal self-discharge level, and prolonged lifespans [2]. Due to the huge potential for storage and extended durability of technologies that store energy, EV efficiency, and performance have significantly improved in recent years. However, the design of EVs with superior reliability and effectiveness of energy control mechanisms is of great significance for researchers and automakers. [3].

However, in applications involving electric vehicles, batteries need to be handled with special attention. The aging procedure of the batteries is significantly increased by inadequate processes, especially over-current, over-voltage, or over-charging/discharging, which also raises the possibility of fire or explosion [4]. Therefore, it is crucial to properly monitor and predict the battery's estimated useful life because an inaccurate capacity estimate might result in overcharging or over-degradation, which could irreversibly harm the battery [5]. The battery pack's remaining usable life is defined as

the quantity of charging and discharging cycles it will go through before reaching an 80% state of health, or before its energy capacity declines to 80% of its original value. Due to the large number of components involved, it is difficult to accurately predict the degradation of a battery's capacity.

Scientists all over the world have dedicated themselves to improving the accuracy and speed of their prediction algorithms to decrease the risk of battery failures because of the importance of these battery health prognostics. It is well-known that these operations must be handled carefully to prevent over-degradation or over-charging, which may seriously harm the battery pack permanently or severely damage its ability to be repaired. Therefore, it is necessary to regularly and adequately analyze the battery lifespan to prolong battery life and control the system effectively [6].

As a result, an effective battery Forecasting and Monitoring System is crucial for assuring protection, prolonging the battery's efficiency, and minimizing the cost and reliability of the system. General forecasting of battery lifespan and monitoring systems [7] primarily comprises various sensors (voltage, current, and temperature), controllers, control circuits, and signal lines, as shown in Fig. 1.1.

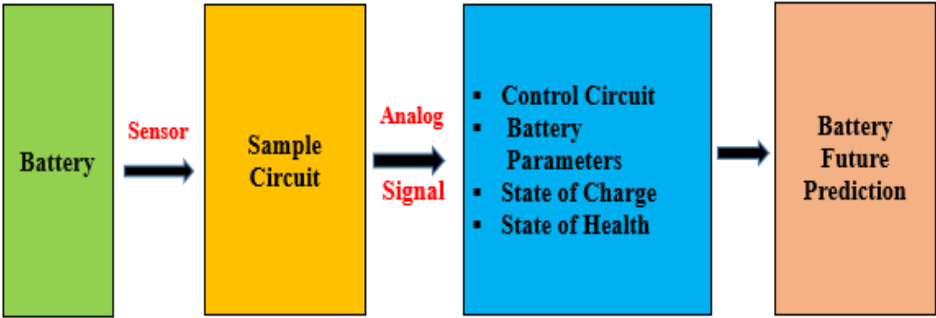


Figure 1.1: Battery Forecasting & Monitoring System

1.1.1 Selection of Method

The State of Health (SOH) factor, which may be predicted using the information on the battery's duty cycle, observed current, observed voltage, observed temperature, observed ambient temperature, charging voltage, charging current, and the measured capacity, describes the battery's health about its idle state. On the other hand, SOH and SOC must be predicted by techniques based on either external or internal battery characteristics involving current, voltage, temperature, and humidity as SOH and SOC cannot be directly examined. Both the operational environment and the state of the battery may have an impact on these parameters. As a result, modeling methods that address the unique

characteristics of the battery are needed. Consequently, it becomes necessary to employ particular estimating techniques [8].

Voltage, current, temperature, electrolyte, and specific gravity can all be utilized to estimate the lifespan of the battery. Previously, carmakers typically utilized Look-up tables (LUTs), whose SOH and SOC performance were plotted throughout the early experimental evaluations carried out in laboratory conditions. The commonly referred to as direct methods are used to carry out these procedures, which rely on testing of the internal resistance or ampere-hour counting and open circuit voltage of the storage device. However, for forecasting battery lifespan, the usage of LUTs may involve significant computational expenses and require the storage of enormous amounts of data in the electronic control module.

Different methodologies use model-based methods to evaluate the battery's SOC and SOH in real-time. The most often used filters are the Kalman filter method and its variants [9], followed by the extended method (EKF) and unscented Kalman filters method (UKF) [10, 11], the adaptive particle filter (APF), the smooth variable structure filter method (SVSF). These techniques can be applied in real-time to smart grids and automobiles. Still, they may have accuracy issues if the model of reference fails to be adequately and precisely calibrated for all possible operational conditions.

Artificial intelligence (AI) is a potential alternative method to get around this limitation. Most of the time, these methods use artificial neural networks (ANNs), which, when properly trained, allow the model to be eliminated while still reaching acceptable levels of accuracy and reliability. The technique for AI-based SOC or SOH forecasting has accumulated plenty of literature [12, 13]. Here, a non-linear model called the artificial neural networks ANN approach will be utilized for forecasting battery lifespan in real-time.

1.2 Problem Statement

First of all, current methods for estimating battery RUL frequently rely on empirical models that don't take into account complicated degradation mechanisms and variability in operating conditions. The complicated connections and temporal dependencies found in battery data are rarely captured by traditional methods of battery SOH estimation, which frequently rely on empirical models or simple statistical techniques. As a result, especially in many different kinds of conditions, these models could fail to provide accurate and reliable predictions. The solutions mentioned above have issues with the

need for greater computer power, a complex algorithm, and a slow response time. Various batteries will have different states of health (SOH), especially if they consume a lot of currents. The development of the battery equivalent model is essential to accuracy. Models with lower accuracy are available.

The second problem relates to the limitations of various approaches that have been used in the literature and may not function well under certain circumstances. Our proposed integration strategy uses a combined strategy to effectively utilize time series forecasting and the LSTM model to increase the overall success rate in order to address these limitations.

1.3 Objectives

This thesis has the following objectives:

- 1) To continuously monitor the battery's current, voltage, temperature, and humidity.
- 2) To ensure the battery's function failure and to optimize the charging and discharging operations.
- 3) To propose a new fast and accurate remaining useful life (RUL) prediction methodology to add an efficient method with real-world applications to the existing literature.
- 4) To ensure battery health and safety.
- 5) To maintain the battery's aging and charging condition.
- 6) To forecast the battery's SOH in real-time.
- 7) To develop a fast response technique for battery life prediction.
- 8) To create a model with excellent accuracy using less computations.

To meet the objective of this project we use ANN and Long short-term memory (LSTM) approaches. For this, ANN is proposed to reliably monitor the Battery's SOH from provided data because of its unique network structure.

1.4 Project Methodology

To develop the system, the following methodology will be used:

- Literature Review
- Develop simulation using AI time series forecasting technique.
- Develop hardware
- Testing

In this project, the battery's State of Health (SOH) is estimated using artificial intelligence (AI) technology. The project's hardware is constructed so that it can provide a real-time dataset with measurements of numerous factors, including battery current, voltage, and temperature, using a variety of sensors. This dataset is used to predict SOH. Fig. 1.2 displays the system's proposed diagram. Numerous current, voltage, and temperature sensors are attached to batteries, and the data from these sensors is retrieved by Arduino. Arduino then receives the data and sends it to the ESP module so that it can be stored as a CSV file. Arduino is further connected to LCD to show real-time data like battery current, voltage, temperature, and battery lifespan (SOH). This dataset is then used in the model's training and testing for the battery lifespan prediction. Here for the forecasting of battery lifespan and monitoring system, battery forecasting algorithms like Simple ANN and Long short-term memory (LSTM) are used.

Battery Forecasting and Monitoring System should include the following function:

- Data acquisition
- Safety protection
- The capacity to predict and determine the SOH.
- An extended battery life.

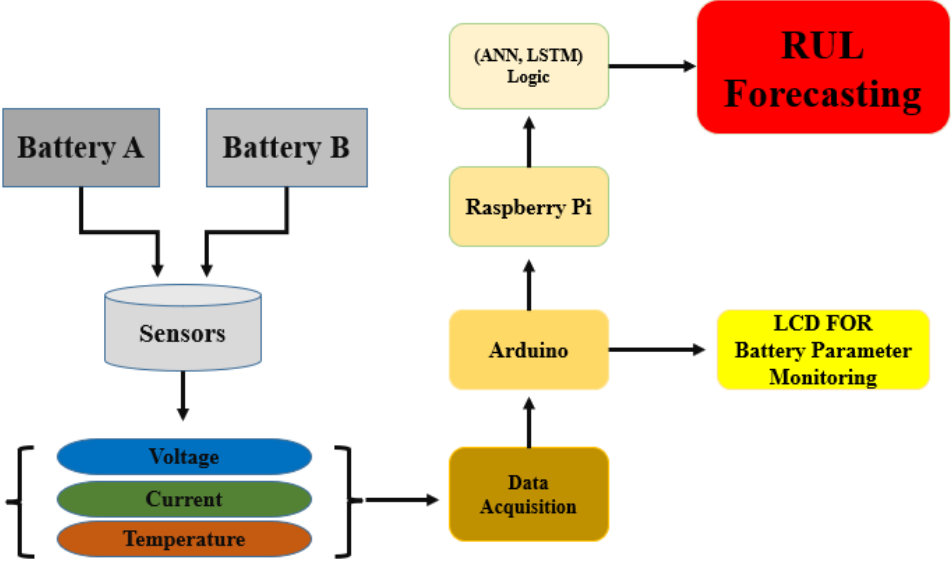


Figure 1.2: Proposed Block Diagram of the forecasting of SOH

1.5 Main Contributions

The following are the project's key contributions. First, the suggested method uses a combined approach of the neural network framework concept and the long short-term memory (LSTM) model to forecast a battery's state of health (SOH). Secondly, the SOH and SOC parameters can be estimated continuously utilizing real-time data retrieved from various types of systems like EVs, grid stations, and solar systems, and the proposed methodologies may yield reliable forecasting results using the battery's current state information. SOH operates as output after the network is trained using inputs like the current, voltage, and varied battery pack temperatures. Third, by accounting for locally minor capacity restoration and the complex information variation during the charging and discharging operation, the proposed LSTM model can precisely and reliably estimate SOH.

1.6 Structure of the Dissertation

In Chapter 2, related works of battery SOH prediction are discussed. In Chapter 3 data collection and the proposed methodology based on ANN and LSTM is introduced. Chapter 4 reports on the hardware implementation, experimental findings, and discussion of SOH. The forecasting of battery lifespan and monitoring system business description model was described in Chapter 5. Chapter 6 concludes with conclusions and provides some suggestions for future research.

1.7 Work Division

Table 1.1 illustrates the responsibilities assigned to each group member as part of the project's SOH forecasting and monitoring system.

Table 1.1: Division of tasks among group members.

Sr.No	Name	Allocated task
1	M Tayyab Mushtaq	Software-integrated design and Documentation
2	Adnan Amin	Hardware design and Documentation.

1.8 Conclusion

This chapter outlined the introduction and project overview and provided a brief explanation of the various battery parameters. The battery pack must be handled cautiously during different operations of batteries to prevent charging excessively or over-degradation, this could seriously impair the battery

pack's ability to be fixed or cause irreversible damage. Therefore, we proposed to design a battery lifespan forecasting and monitoring system using Artificial Intelligence techniques that are crucial for assuring safety, prolonging battery life, and lowering the cost and durability of the system. Further problem statements and project methodology were discussed in this chapter to better understand the project.

CHAPTER 2

LITERATURE REVIEW

The demand for quick and accurate SOH prediction algorithms has contributed to the development of numerous techniques throughout the years. The literature on battery SOC and SOH prediction algorithms will be reviewed in this chapter.

By reviewing the aging process of batteries, many methods are currently presented for predicting the SOH and SOC in the literature. This comprises several elements, from the physical measurement to the theoretical model. In recent years, several techniques have been put out to forecast battery SOH, which may generally be broken down into three categories [14]: model-based techniques, direct techniques, and data-driven techniques.

2.1 Direct Approach

The two primary estimating methodologies were previously known as open circuit voltage-based and coulomb counting approach. Coulomb counting offers a direct evaluation approach by draining the battery until it reaches a SOC level of 0% and dividing the quantity of charge released by the capacity that is nominal to determine SOH [15]. The Coulomb counting technique is commonly employed due to its low power usage benefit. Still, it needs to be more adequate due to its substantial estimation error of roughly 10%, although the accuracy can still be enhanced through the addition of a Kalman filter. Although it is simple to build, this open-loop estimator might be biased as a result of incorrect SOC configuration. Additionally, the estimated error raises due to the limited sensor accuracy.

The Open Circuit Voltage (OCV) approach, assesses battery decaying properties at various temperatures during operation using Incremental Capacity Analysis (ICA) and can assess SOH in both online and offline modes. The open circuit voltage (OCV) approach approximates the SOC through the monotonic relationship between both SOC and its OCV [16]. The approach is not appropriate for onboard implementation since measuring the OCV needs the battery to be isolated from the loads for a duration greater than 2 h to settle a steady state level. This technique is straightforward and quick, but a lot of time is required for battery standing to make sure that the measured voltage is equivalent to OCV. Therefore, it cannot simulate a battery's long-term steady discharge.

The method for accumulating electric charge that is currently most often employed is the Ampere-hour (Ah) integral approach. Its basis is the estimation of the amount of electricity used while charging

and discharging. When determining SOC, we additionally consider the temperature and the battery's efficiency when charging and discharging [17]. The simplicity of calculation, stability of the algorithm, and online measurement are benefits of the Ah integral approach. It is also clear that this approach has a drawback. First, there is always a potential for errors as the amount that requires to be determined is very large and essential. Second, when the battery is used, it ages and the capacity loss is irreversible. Additionally, the capacity of battery during the action of discharging may be regained, still the influence on the capacity when charging is difficult to remove. Finally, as time passes, the measurement error will increase.

Many researchers are now working to develop new techniques dependent upon the ampere-hour integral approach to improve the accuracy of SOH. One of these methods combines the Ah integral approach with the OCV strategy, which employs OCV to modify the initial SOC in order to improve estimate accuracy [18].

In previous years, carmakers typically utilized Look-up tables (LUTs), whose SOH and SOC performance were plotted throughout the early experimental evaluations carried out in laboratory conditions. The commonly referred to as direct methods are used to carry out these procedures, which rely on testing of the internal resistance or ampere-hour counting and open circuit voltage of the storage device. However, for forecasting battery lifespan, the usage of LUTs [19] may involve significant computational expenses and require the storage of enormous amounts of data in the electronic control module.

Direct analysis techniques have the benefit of lower computing expenses and energy consumption, including Coulomb Counting, the Open Circuit Voltage approach, and building an electrochemical framework. While some of these techniques can be utilized offline as well as online, their forecasting errors are generally less reliable than those made by different types of forecasts algorithms. Additionally, the above-mentioned approaches are difficult to implement in practical applications and have been restricted by the processing power of BMS. These techniques have largely been replaced by more advanced ones since they are acknowledged to have certain drawbacks.

2.2 Model Base Approach

Model-based approaches carry out the SOH estimation by creating a battery model and discovering fluctuations of the linked parameters, representing an important path for exploring battery degradation. The three models that are used the most frequently are empirical degradation techniques, equivalent

circuit models (ECM), and electrochemical techniques [20]. When analyzing the battery's operating law during degradation from an electrochemical standpoint, the electrochemical model has to be included all related features, including the battery's value of the voltage, flow of current, diffusion factor, temperature and humidity, and chemical concentration. The fluctuation of the mechanical and chemical configuration of the electrodes that are positive and negative are examined in detail [20], where a comprehensive mechanical and chemical degradation mechanism is presented for the forecast of the lifespan of the battery. According to experimental findings, the battery's internal structure cracks and expands, a solid electrolyte interphase (SEI) coating grows on the newly damaged surface, and the battery's capacity decreases as a result. Despite having a high forecast accuracy, this approach requires several derivations and computations. The model-based approach may adequately depict the battery's mechanical and chemical characteristics, but the parameters used might have a big effect on the model's reliability and stability [21].

Different methodologies use model-based methods to evaluate the battery's SOC and SOH in real-time. The most often used filters are the Kalman filter method and its variants, followed by the extended method (EKF) and unscented Kalman filters method (UKF), the adaptive particle filter (APF), and the smooth variable structure filter method (SVSF). A SOC estimate approach utilizing an Extended Kalman filter (EKF) was proposed by Rzepka et al [22]. In order to evaluate the feasibility of the suggested EKF approach, they evaluated the untuned EKF approach against the EKF approach modified using the noise parameter Q . According to the experimental findings, the adjusted EKF model performed well, with an error of just about 1% compared to the untuned EKF model's 4%. Although, the error indicates, the EKF is very sensitive to noise and that the condition of the battery might vary due to degradation, which would make it harder to estimate the battery's performance.

A dual-adaptive EKF-based SOC and SOH estimate approach was put out by Li et al. [23]. The approach suggested improved estimate performance by merging the predicting error of the voltages at the terminals and the capacity of the battery data from the model of the equivalent circuit into a filter having a prediction reliability of less than one percent. The authors emphasized that computational challenges must be taken into account when using battery deterioration and that decay of the battery was not assessed.

The performance of the model-based technique for estimate is reasonable, despite the fact that a lot is based on the caliber of the battery characteristics. The model-based method demands in-depth subject expertise, a long development period, and greater computational resources.

2.3 Data-Driven Approach

This section will go through some of the developments made in the literature on predicting the battery's remaining useful life using data-driven methods. These techniques create algorithms that attempt to connect the input characteristics and their impact on the output SOH prediction using monitoring data from battery cycling. These models may be theoretically defined using linear components, but because of their depth and complexity, these techniques can also be utilized to identify non-linear relationships between variables.

According to the operational data acquired, the data-driven approach directly tracks the variation in battery longevity, from which the SOH may be evaluated [24], [25]. It ignores the complex chemical as well as physical reactions that occur within the battery. Investigators do not need to simulate the mechanical features of the degradation of the battery, which is a significant benefit of the data-driven approach. In contrast, using an algorithm based on machine learning or an oriented analysis of data technique, one may quickly develop a black-box structure utilizing the input data of electrical parameters and the outcome of SOH.

Data-driven strategies for SOH prediction, such as those based on fuzzy measures and machine learning, have gained popularity in recent years. Common data-driven methods include the Support Vector Machine (SVM) algorithm [26], Gaussian Process Regression (GPR) [27], Particle Filter (PF) [28], and Random Forest Regression (RFR) [29]. Based on the characteristics of the voltage required to charge the curve, a Support Vector Machine (SVM) algorithm containing multiple voltage levels is created. The grid search technique utilizing cross-validity is then used to improve the variables of the model and identify the best voltage range for SOH prediction.

This method has the benefit of taking less development time and requires less specialized knowledge. Without knowledge of the battery's parameters, data-driven techniques can identify battery degradation trends, but they come at a high computational cost. Additionally, these data-driven techniques are difficult to apply in practical applications and are constrained by the BMS's high computing requirements.

Classic machine learning algorithms have also been applied in prior techniques. These methods have the advantage of being able to self-learn SOC estimates without the requirement for manually created models since they can be trained using real-world data. However, when neural networks were employed alone, the results were frequently insufficiently accurate, requiring the use of Kalman filters or other inference techniques to attain the necessary estimation accuracy. Modern machine learning algorithms are developing more quickly than ever because of ever-expanding processing power and easier access to huge quantities of data. Algorithms for machine learning become increasingly frequently utilized in our daily lives.

Hybrid strategies that merged ANN with other techniques like Extended Kalman Filters (EKF) [30] have also been examined with the aim to make sure the energy storage system's effective dynamic operation. In this work, reliable SOC estimates with a 1% estimated error were established. In an experiment using Unscented Kalman Filters (UKF) along with ANN [30], M. Pecht, C. Chen, N. Williard, and W. He sought to enhance estimation reliability and decrease estimation fluctuation with respect to the Li-Ion battery mechanism. The algorithm displayed an RMS error of about 2.5% along with a maximum margin of error of 3.5% during different temperature readings.

Table 2.1 represents the comparison of different techniques used for SOH forecasting and their limitations.

Table 2.1: Literature Review Summary

Sr.No	Ref.	Key Contribution	Techniques	Limitations
1	[14]	Online state-of-health estimation for lithium-ion batteries using constant voltage charging current analysis.	Time constant of CV charging current analysis.	It is hard to determine a balance between several goals, such as charging rate, loss of energy, and variations in temperature.
2	[15]	Battery pack state of health estimation using artificial intelligence optimization algorithm.	Particle swarm optimization genetic algorithm (PSO-GA) estimator.	During a working period, the battery pack's SOH will fluctuate, especially while it is using a lot of electrical power.
3	[16]	A study on the impact of open circuit voltage tests on state of charge estimation for lithium-ion batteries.	Open circuit voltage (OCV) method.	The prediction is not suggested for continuous long-term discharging since it does not take the charging process into consideration.

4	[17]	SOC Estimation and Simulation of Lithium Battery Based on Improved Ampere-hour Integral Method.	Ampere-hour (Ah) integral algorithm.	Typically, the impact is better within a specific time of battery estimation.
5	[22]	Dual extended Kalman filter for battery state-of-charge and state-of-health estimation.	Kalman filter technique.	Sensitive to model accuracy.
6	[24]	A battery health monitoring method using machine learning data driven approach.	Data driven method.	More computing resources required. Complex calculation and slow response.
7	[31]	Combined Estimation of Battery State of Charge and State of Health Based on AI.	Artificial neural networks approach.	Sensitive battery prediction accuracy.
8	Proposed Methodology	Forecasting of battery lifespan and monitoring system using artificial intelligence.	LSTM neural network	Better accuracy and less computational time.

2.4 Conclusion

In this chapter, a literature review was presented regarding the RUL prediction, mainly for lithium-ion batteries. Different methodologies were observed, and research gaps were then discussed. It was found, majority of methods can be divided into two distinct groups: model-based and data-driven; however, several recent publications have combined these two approaches into hybrid ones in an effort to overcome the drawbacks of each methodology. In general, the model-based procedure requires a significant amount develops expert knowledge and is generally less flexible than data-driven methods. On the other hand, machine learning typically outperforms conventional model-based methods in terms of accuracy when applied to recognizing the non-linear connection across the output and a specific collection of input factors. However, the developed data-driven methodology's resilience depends critically on the dataset's quality. The proposed LSTM algorithm has the ability of better accuracy and less computational time.

CHAPTER 3

DATA COLLECTION AND METHODOLOGY

The battery model for the prediction of battery lifespan depends on the aging dataset of batteries from NASA and which has become a strongly recommended and often applied resource by numerous scientists to obtain SOH and battery remaining lifespan predictions. Here, one of the most promising ANN models including long short-term memory (LSTM) networks is utilized because of their capacity to recognize temporal correlations and patterns in data. To remove any outliers or missing values, the data is carefully filtered and preprocessed. After that, the obtained dataset is used to train an LSTM model using a sequence-to-sequence methodology, in which the model is given a series of input data and forecasts the RUL of the battery at each instant in the sequence. The resulting model can quickly and precisely estimate the remaining lifespan (SOH) of batteries, giving significant details about battery performance and maintenance.

3.1 Data Collection & Proposed Framework

The battery datasets, which contain three distinct functioning characteristics for charging performance, degradation performance, as well as resistance under the ambient temperature, are taken from the dataset of NASA [32] and are used in this project. Batteries are charged using the stable-current, stable-voltage (CCCV) approach, which involves driving the current in batteries under a level of 1.5 A until the voltage inside the battery approaches an optimal level near 4.2 V, at which time the voltage level stays steady unless the amount of current is reduced around 20 mA. The NASA Battery dataset is formed of a number of sub-datasets, each of which includes data about a single battery. Each sub-dataset is made up of various kinds of files, such as time-series data for different characteristics including capacity, current, voltage, and the temperature, as well as metadata files containing further details on the battery, such as its model number, manufacturing date, and test conditions.

The dataset's collection of data from batteries subjected to different stresses is an important feature that makes it an accurate representation of battery degradation in practical applications. The data is obtained on a consistent basis, enabling analysis of the temporal evolution of battery characteristics over time. The dataset consists of data from batteries with varied degrees of degradation, from healthy batteries to batteries on the verge of failure, which is a further important aspect of the battery dataset.

This makes it possible to develop models that accurately forecast battery RUL, which is a critical parameter to make sure that battery packs are secure and reliable.

Fig.3.1 shows the suggested architecture for multifaceted charging strategies according to LSTM for the forecasting of the battery's remaining lifespan. There are three phases in this battery forecasting framework:

- Pre-processing of the data
- Training
- Testing.

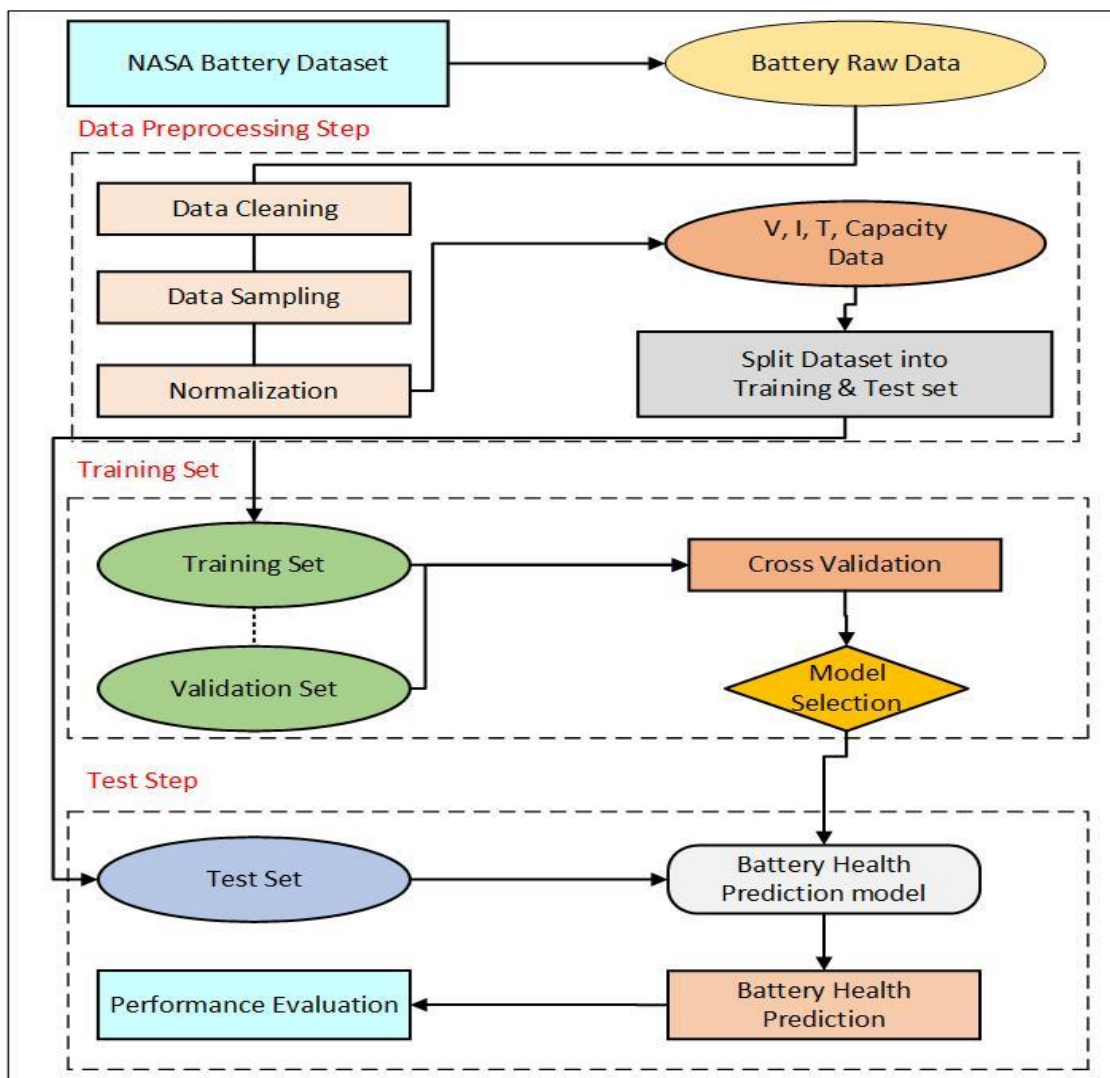


Figure 3.1: The proposed architecture of the forecasting of the battery lifespan system

We first remove irregular information by data purification process, and then average the remaining information throughout a sample duration to avoid fluctuation in brief intervals of time. In order to do this, several data cleaning and filtering procedures must be used, including removing outliers, the input of missing data, and the use of smoothing algorithms. Several parameters are extracted from the raw data after preprocessing, including the state of charge, resistance, and state of health of the dataset.

After preprocessing, min-max normalization is carried out, and the resulting dataset has been classified into training data, validation data, and test data. In this subsequent phase, the structure of the model is selected after the cross-validity of the hyperparameters. By utilizing the algorithm designed in the preceding phase, the final phase involves executing the RUL forecasting and proceed evaluation for performance.

3.2 Techniques

3.2.1 Artificial Neural Networks (ANN)

The word "Artificial Neural Network" was inspired by neural networks from biology, which describe the organization of a person's brain. Similar to how cells are linked together in the real brain's activity, artificial neural networks have neurons that have connections to each other through several levels of the structures. Artificial Neural Networks (ANNs), a form of machine learning strategy, have been created to replicate the framework and functioning of the brain of a human being. ANNs are composed of layers of linked nodes (also known as neurons) that are trained to determine patterns in data. Every neuron receives input signals from other neurons or from the outside environment and computes an output signal based on the intensity of those inputs and the internal parameters of the neuron, which is then sent to other neurons.

Numerous artificial neurons, or units, arranged in a hierarchy of layers make up a neural network. An artificial neural network can have several layer types, as seen in the image below.

Input Layer:

As suggested by the title, it takes instructions as input from the developer in a number of formats.

Hidden Layer:

The hidden layer lies through the input and output layers of the model. This offers every calculation necessary to look for hidden characteristics and patterns.

Output Layer:

The output is finally communicated using this layer after the input performs a series of modifications using the hidden layer.

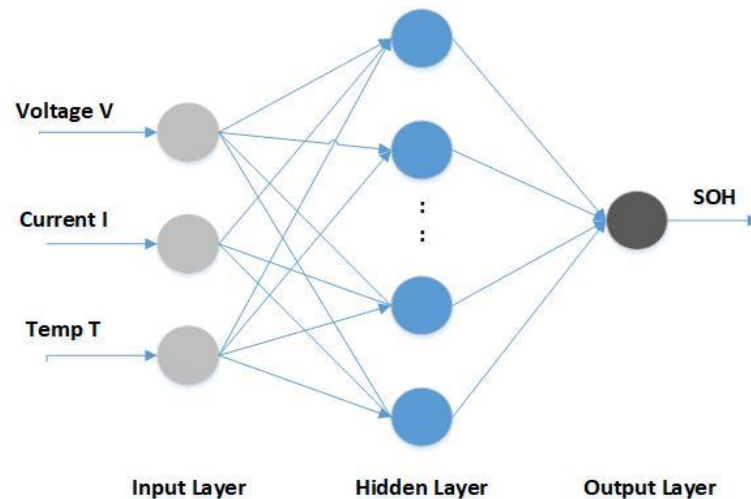


Figure 3.2: ANN Layers

There are different neural networks available that can help to solve different forecasting problems.

- **Feed-Forward Neural Network:** Designed to solve generic difficulties with classification as well as regression.
- **Convolutional Neural Network:** Employed in the categorization of images and the object recognition problem.
- **Deep Belief Network:** Designed to diagnose cancer in the medical field.
- **RNN:** Used for natural language processing, time series forecasting, voice recognition, and speech recognition.

3.2.2 Recurrent Neural Network (RNN)

Recurrent neural networks (RNNs) are a form of a network of neurons in which the outputs of previous phase are used as inputs for the next phase. RNNs have a concept of "memory" that remember all data regarding calculations made up to time step t . Recurrent neural networks (RNNs) get their moniker from the fact that their neurons continually execute a similar function for each

element in a particular order, despite the outcomes relying on previous estimations. This reduces the complexity of the parameter set relative to different neural networks.

A recurrent neural network (RNN) is a sort of artificial neural network that performs well for time-series forecasting. RNNs have feedback connections, in contrast to feedforward networks, which enable them to analyze sequential input and detect temporal relationships. They are therefore perfect for modelling and forecasting trends, patterns, and other phenomena that rely on time. This makes it possible for the network to recognize long-term dependencies and provide outputs that are impacted by previous inputs. RNNs can be trained on previous data sets to forecast future values of a time series.

RNNs is a strong tool for the time-series forecasting because they can capture complicated patterns and dependencies that other approaches might overlook. To prevent overfitting and to produce accurate and reliable forecasts, they must be carefully tuned and validated.

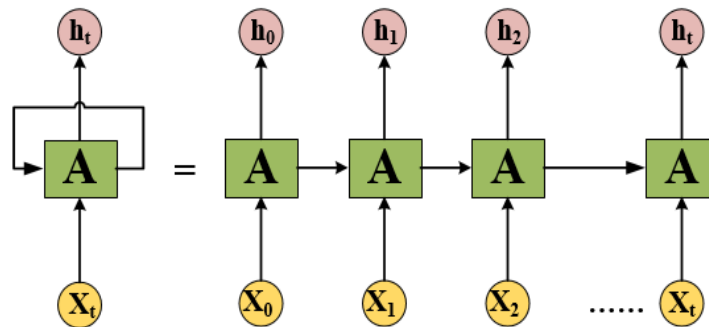


Figure 3.3: Basic architecture of Recurrent Neural Networks

An RNN is unfolded into a complete network in the figure above. Unfolding means that we repeating the same network's layer structure over the whole sequence.

Limitations of RNN

- Gradient vanishing and exploding are issues with RNN.
- An RNN's development is a challenging endeavor.
- Tanh or Relu are unable to manage lengthy patterns as the activation function.

3.2.3 LSTM

A special kind of RNN capable of acquiring dependency relationships over time is termed as a Long Short-Term Memory network (also referred to as "LSTM"). They were initially proposed by

Hochreiter & Schmidhuber (1997) and greatly improved and popularized in the subsequent work. LSTM is now a frequently used technique and performs incredibly effectively on a wide range of problems.

A certain kind of recurrent neural network (RNN) named Long Short-Term Memory (LSTM) is especially helpful in forecasting time series data. Traditional RNNs have certain drawbacks, including the potential for the vanishing gradient problem while processing long data sequences. LSTMs were developed to address these issues. The ability of LSTMs to retain and retrieve data over a longer period of time is one of its fundamental characteristics. They accomplish this by using memory cells, which are a form of long-term memory. Using a variety of gating methods, the memory cells are modified in every step according to the current input and past data.

3.3 Mathematical Modeling

Long-term short-term memory (LSTM) mathematical modeling for time series forecasting of SOH of battery involves representing the different components of the LSTM model as a set of mathematical equations. Here, Fig. 3.4 represents the basic architecture regarding the LSTM neural network technique.

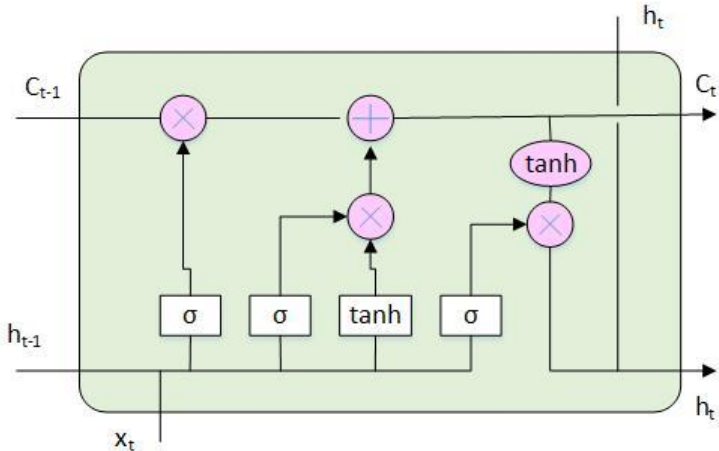


Figure 3.4: Architecture of LSTM

Like any other normal neural network, LSTMs are nothing more than a stack of neural networks with linear layers made up of weights and biases. Backpropagation is used to continuously update the weights. Here, we address a few key terminologies that are specific to LSTM:

1) **Cell:** In the LSTM network, a "cell" refers to each unit. Every single cell has three inputs and two outputs.

- X_t — the input at step t in the period
- h_{t-1} — Prior hidden position
- C_{t-1} — prior cell position
- h_t — the modified hidden state which is utilized to forecast the result
- C_t — The current state of cells.

2) **Gates:** For the control of the memorization process, LSTM employs a unique theory. The LSTM's gates, also known as the gating mechanism, convert analog memory components into probabilistic scores by performing a point-by-point process of multiplication with an activation function that is sigmoid that saves the outcomes in the 0–1 interval. Gates regulate the flow of data to and from the LSTM neurons.

Only one LSTM cell contains four distinct gates.

- Input gate
- Forget gate
- Cell state
- Output gate

Forget gate

The forget gate decides whether details should be removed through the memory cell. Dashed lines in Fig.3.5 show the forget gate of LSTM architecture.

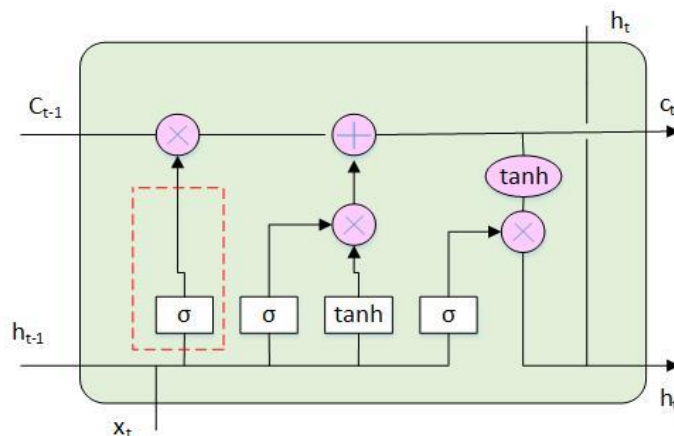


Figure 3.5: Forget gate of LSTM

The forget gate performs a function of sigmoid activation on the taken values, taking as inputs the present input along with the prior hidden value. The resultant of the function known as the sigmoid is multiplied with the current value of the memory cell to figure out which data should be discarded using the following equation:

$$f_t = \sigma(W_f \cdot [h_{t-1}, x_t] + b_f) \quad (3.1)$$

Here, σ is a sigmoid activation function, W_f is a weight matrix, $[h_{t-1}, x_t]$ is the concatenation of the previous hidden state and the current input, and b_f is a bias vector. As a result, the LSTM could decide to forget the information detail that is no longer useful to the current task.

Input Gate

The input gate decides how much part of the data should be saved within the memory cell. Here dashed lines in Fig. 3.6 represent the input gate of LSTM architecture.

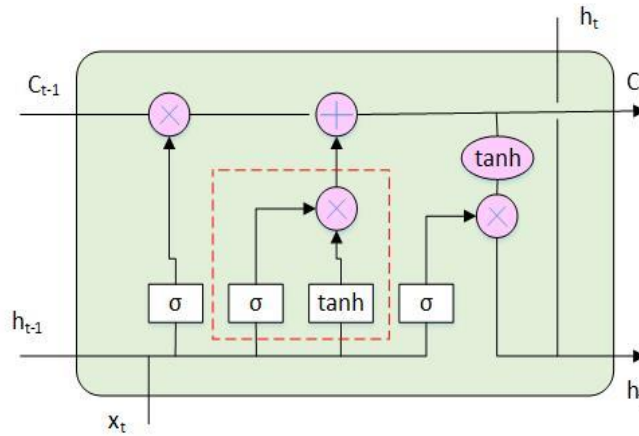


Figure 3.6: Input gate of LSTM Architecture

It provides an output vector i_t that is a value between 0 and 1, reflecting the amount of new input to keep, by using the prior hidden state h_{t-1} along with the present input x_t act as inputs. This gate is modeled as follows:

1. The input gate accepts an accumulation of the prior hidden state h_{t-1} and the present input x_t as input:

$$i_t = \sigma(W_i \cdot [h_{t-1}, x_t] + b_i) \quad (3.2)$$

Here, W_i is a weight matrix and b_i is a bias vector. The σ is a sigmoid function, that compresses the input integers from 0 to 1.

2. And in to calculate a candidate cell state:

$$\tilde{C}_t = \tanh(W_c \cdot [h_{t-1}, x_t] + b_c) \quad (3.3)$$

Here, W_c is a weight matrix and b_c is a bias vector. The \tanh is a hyperbolic tangent function, that compresses the input integers from -1 to 1.

3. To decide the new input that must be recorded within the memory cell, the input gate and the candidate cell state are multiplied element-wise:

$$C_t = i_t * \tilde{C}_t \quad (3.4)$$

Here, $*$ denotes element-wise multiplication.

In short, an LSTM's input gate utilizes a sigmoid function to decide how much of the current input to keep and a candidate activation vector to decide a new input to add to the memory cell. By evaluating which parts of the incoming input to keep, an LSTM can successfully simulate dependencies that last in sequences of data.

Cell state

An LSTM's memory is composed of a cell state. When dealing with longer input sequences, they perform noticeably better than standard RNNs in this area. At every time interval, the prior cell state (C_{t-1}) integrates along with the forget gate to examine which data is to be passed forward then it integrates using the input gate (i_t and \tilde{C}_t) to produce a new cell state or new memory cell using the following equation:

$$C_t = f_t * C_{t-1} + \tilde{C}_t \quad (3.5)$$

In conclusion, the input, forget, and output gates are employed to store specific data and eliminate data to update the cell state of an LSTM continuously. The network can successfully simulate long-term dependencies in a sequence of data because of the cell state's ability to store information for a longer period of time.

Fig below shows the cell state of an LSTM architecture.

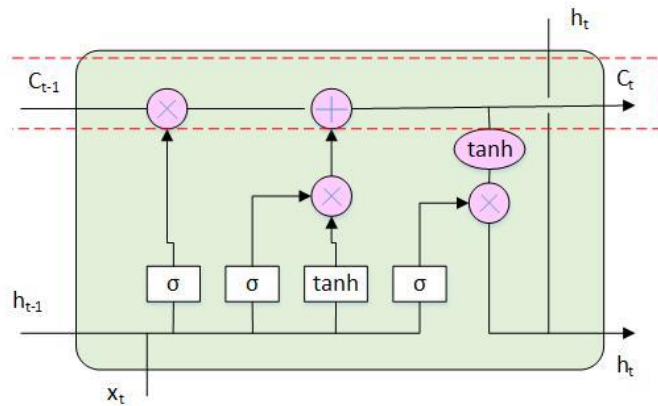


Figure 3.7: Cell State of LSTM

Output gate

The LSTM technique's output is determined by the output gate. The output gate of the neural network using the LSTM is represented by the dashed lines in Figure 3.8.

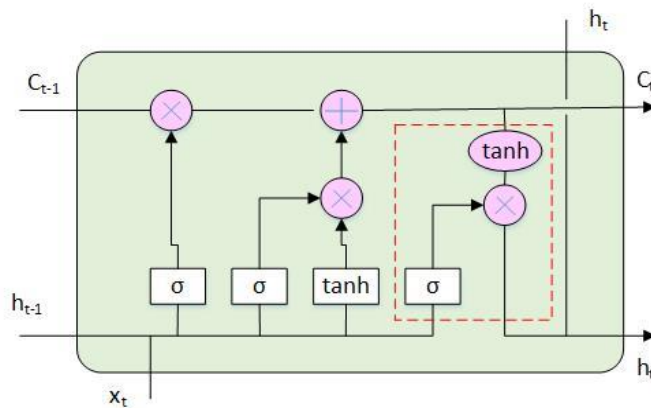


Figure 3.8: Output gate of LSTM Architecture

The output gate accepts the present input and the prior hidden state as input and then performs a sigmoid activation function on the input values. The memory cell's current value is multiplied by the sigmoid function's output, and the resulting values are then put through a tanh activation function to bring them into the -1 to 1 range. The outcome of the LSTM in the current time period is obtained using the following equation.:

$$O_t = \sigma(W_o \cdot [h_{t-1}, x_t] + b_o) \quad (3.6)$$

$$h_t = O_t * \tanh(C_t) \quad (3.7)$$

Here O_t is the output gate, W_o is a weight matrix, and b_o is a bias vector and h_t is the current hidden state. After that, a dense layer receives the LSTM layer's output and transforms it to the desired output format.

3.3.1 Proposed LSTM Model for RUL Prediction

A single form of sequence information is used for training a one-to-one structure. However, if there aren't enough training data, it could not be effective for RUL prediction. Furthermore, additional data like current, temperature, and voltage are not suitable for input. So, we presented using a different architecture illustrated in Figure 3.9. This many-to-one architecture significantly decreases the total quantity of parameters by associating four various kinds of input variables (capacity, temperature, current, and voltage) to only one result (capacity).

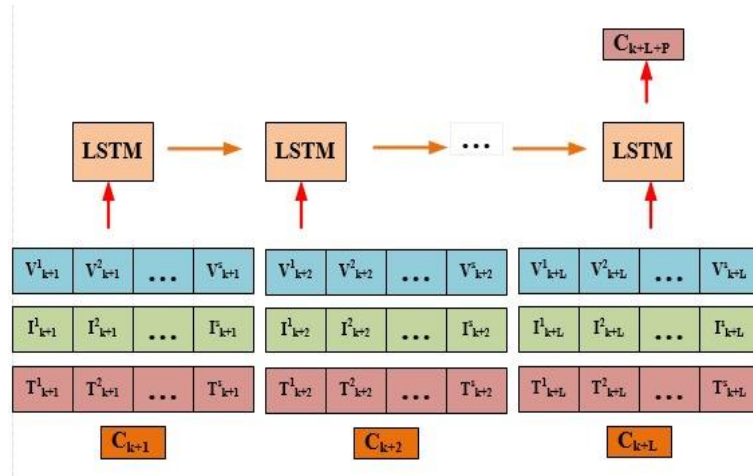


Figure 3.9: Many-to-one Structure

MC-LSTM

Voltage, current, and temperature multi-channel charging characteristics described below are included in the proposed model's input along with the capacity:

$$D_n = \begin{Bmatrix} V_n^1, V_n^2, \dots, V_n^k \\ I_n^1, I_n^2, \dots, I_n^k \\ T_n^1, T_n^2, \dots, T_n^k \\ C_n \end{Bmatrix} \quad (3.8)$$

Here V_n^k , I_n^k , and T_n^k are the k^{th} represent the voltage, current, and temperature samples respectively and K is the total number of spots for sampling across one charging description. The presented technique, known as multi-channel LSTM (MC-LSTM), can incorporate a number of factors that influence capacity change.

3.3.2 Layers of LSTM Model:

A typical LSTM model for time series forecasting contains numerous layers, each of which performs a particular task. The LSTM models for time series forecasting for SOH have the following common layers:

1. Input layer: The input layer is the primary layer of the LSTM model to receive the provided time series data. A number of neurons are often present in the input layer, each of which is associated with a particular feature of the incoming information.
2. LSTM layer: The foundational element of the LSTM model is the LSTM layer. It has many LSTM cells that are responsible for handling the input data processing and producing predictions from the output. Every LSTM cell contains three gates: an input gate, a forget gate, and an output gate. The cell state, which keeps the relevant information from the prior step, is also present in each LSTM cell. These gates control the information flow across the cell state and help the LSTM model to determine the long-term dependencies in the given data.
3. Dropout layer: The LSTM model's overfitting is prevented by using the regularization approach known as Dropout. The dropout layer drives the model to develop more reliable and generalizable representations of the data by randomly dropping out some of the neurons from previous layers during training.
4. Dense layer: The LSTM model's last layer, the dense layer produces the output predictions. The dense layer includes a lot of neurons, each of which corresponds to a separate output time step. The output of the dense layer is generally a single scalar value that describes the predicted number for the next time step t .

3.4 LSTM algorithm steps:

Recurrent neural networks, especially the LSTM (Long Short-Term Memory) method, are typically employed for the prediction of battery RUL due to their ability to control the sequential nature of battery data. For the prediction of battery RUL using LSTM Here following steps involved:

1. Data preparation: Obtain the dataset for the batteries and pre-process the data by carrying out operations including feature extraction, normalization, and data cleaning. Create training, validation, and test sets from the data.
2. Define the LSTM model's architecture: Specify the LSTM model's hidden layer, neuron, and activation functions for each layer. Define the optimizer and loss function as well.
3. Train the model: Set the number of batches as well as the epoch count before fitting the LSTM model to the training set. To determine whether a model is overfitting or underfitting, examine its performance on the validation set.
4. Evaluation of the model: Measurements like the mean absolute error (MAE), R square value, and root mean square error (RMSE) are computed when the model is tested on the test dataset.
5. Predict RUL: After the model has been trained and verified, use it to calculate the battery's remaining useful life (RUL).
6. Model tuning: If the LSTM algorithm's efficiency is unsatisfactory, modify the algorithm's parameters and hyperparameters, which include the selection of hidden layers or the learning rate, and repeat the training and evaluation procedures until the desired performance is obtained.

3.5 Model Evaluation

The accuracy of the model for the forecasting of battery lifespan (SOH) depends on input characteristics including voltage, current, temperature, capacity, and cycle index. A number of measures, including MAE, MSE, RMSE, R-squared, accuracy, and F1 score, can be employed to evaluate the efficiency of the LSTM algorithm. The particular problem and the sort of data being used determine which metrics to be employed. The equations for RMSE are:

$$RMSE = \sqrt{\frac{1}{n} \sum_{n=1}^n (y_n - \hat{y}_n)^2} \quad (3.9)$$

Here y_n is the measured capacity, \hat{y}_n is the predicted capacity, and n is the cycles of the battery.

Here, we divided the battery dataset into training, validation, and testing datasets to determine the accuracy of the LSTM algorithm for battery lifespan (SOH) prediction. The target variable (RUL) and input characteristics are used to train the LSTM model utilizing the training set. The validation set is employed to modify the LSTM algorithm's hyperparameters, and the training phase of the model's progress is assessed. Considering the testing data set, the trained LSTM algorithm's overall accuracy is assessed.

After LSTM models training, we use the testing set to predict the lifespan of the battery packs and compare the predicted values with the actual SOH values. Then, one or more evaluation measures, such as RMSE, MAE, and R-squared, are utilized to assess the efficiency of the LSTM model. A good LSTM model for predicting battery SOH should have less MAE, MSE, and RMSE values, and high R-squared and accuracy values. If the LSTM model's performance is unsatisfactory, we modify its hyperparameters or try various LSTM architectures in order to make better performance.

3.6 Data Collection and Analysis

We are using the battery datasets, which contain three distinct functioning characteristics for charging performance, degradation performance, as well as resistance under the ambient temperature, taken from the dataset of NASA [32] and are used in this project. Batteries are charged using the stable-current, stable-voltage (CCCV) approach, which involves driving the current in batteries under a level of 1.5 A until the voltage inside the battery approaches an optimal level near 4.2 V, at which time the voltage level stays steady unless the amount of current is reduced around 20 mA. For the battery dataset, we use batteries #5, and#6 of the NASA datasets, in which degradation of batteries happens at 2A steady current unless the battery voltage reduces to about 2.7V as well as 2.5V for both batteries.

The capacity used to define the state of health (SOH) for the purpose of calculating battery discharging is:

$$SOH(\%) = \frac{C_m}{C_i} \times 100 \quad (3.10)$$

where C_i is the rated capacity along with C_m is the observed capacity for battery cycle n . Beginning from the several given capacities, the batteries capacity regularly reduces with respect to time, charging profile, discharging profile, and the resultant capacity of both batteries #5, and #6 is 70.5% and 57.7% respectively.

Depending on the application, a battery's life is considered to be ended when its remained capacity reaches 70 to 80% of its rated capacity. To make the most of the two battery datasets, we selected the last stage lifespan as the highest possible storage at the final cycle.

The capacity change for each cycle for the two batteries is shown in Fig.3.10, to show the trend of change in each battery, which enables a more thorough analysis of the predictions. Data cleaning must be done first in order to acquire the two capacity degradation curves illustrated in Fig. 3.10. Here, averaging highly correlated data is used to replace abnormal values before integrating capacity degradation data in the experiment.

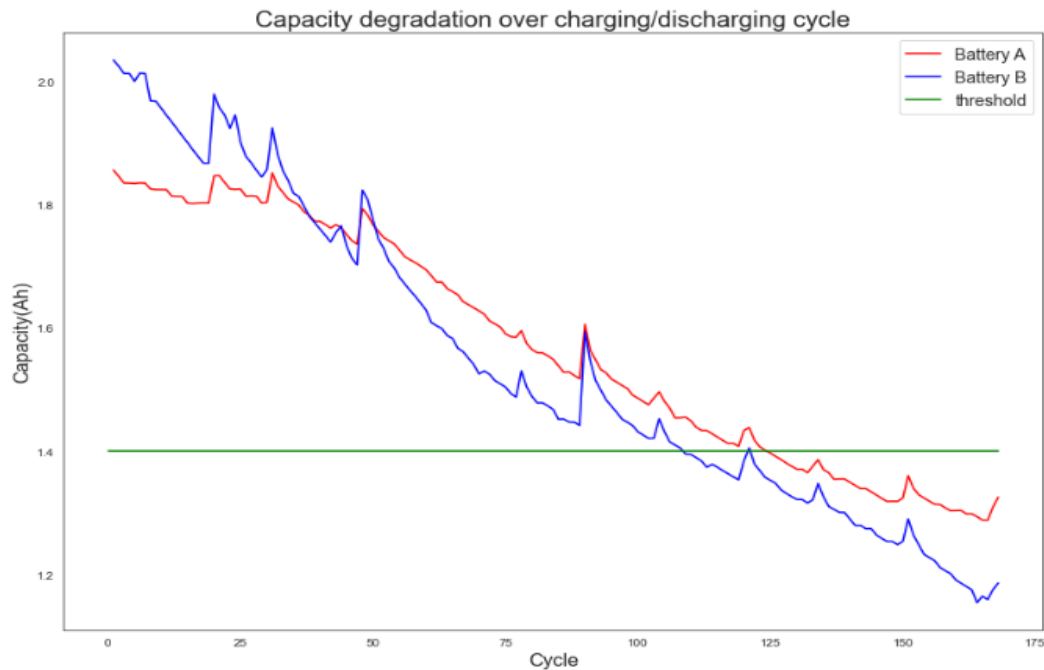


Figure 3.10: Battery A & B plotted (Capacity vs Cycle)

Figure above shows the capacity degradation over the cycle. In this case, the horizontal line denotes the threshold at which the battery's life cycle can be said to have ended. The analysis clearly shows an overall decline in the battery degradation with a few irregular peaks in between.

3.6.1 SOH Calculation

Since the deep learning model will be used to predict the battery lifespan (SOH), so it is important to compute the battery lifespan by using the SOH equation for the initial and measured value of capacity using the NASA dataset capacity values. Similarly, after SOH is calculated, a graph of SOH for each cycle is developed, with the horizontal line indicating the 70% threshold at which the battery has completed its life cycle, and a replacement is recommended.

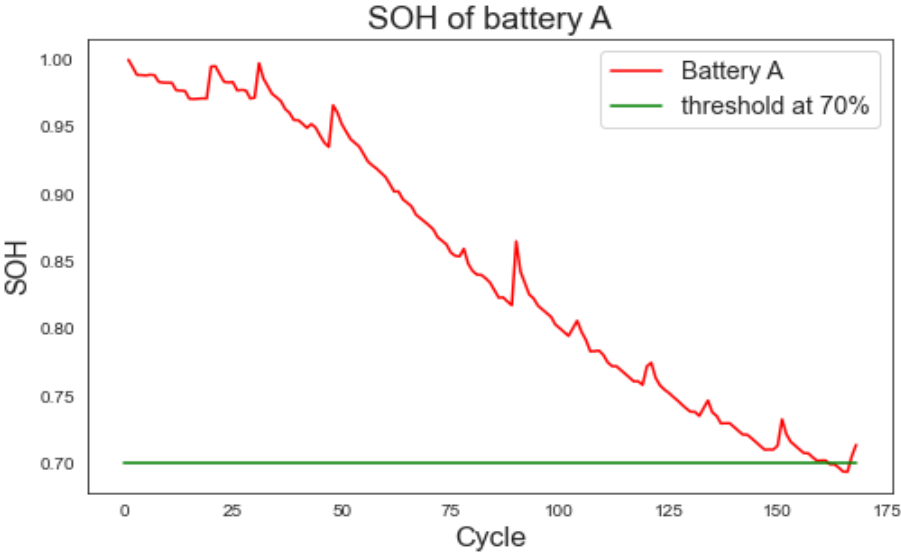


Figure 3.11: SOH of battery A

3.7 Results

A same algorithm is developed utilizing the Adam optimizer and backpropagation parameters to estimate the SOH of the battery. There are 1124201 parameters that are taken into consideration during training. There are four LSTM layers, one dense layer, and four dropout layers for the development of model shown in Fig. 3.12.

```
Model: "sequential_1"
```

Layer (type)	Output Shape	Param #
lstm (LSTM)	(None, 10, 200)	161600
dropout_1 (Dropout)	(None, 10, 200)	0
lstm_1 (LSTM)	(None, 10, 200)	320800
dropout_2 (Dropout)	(None, 10, 200)	0
lstm_2 (LSTM)	(None, 10, 200)	320800
dropout_3 (Dropout)	(None, 10, 200)	0
lstm_3 (LSTM)	(None, 200)	320800
dropout_4 (Dropout)	(None, 200)	0
dense_4 (Dense)	(None, 1)	201

```

=====
Total params: 1,124,201
Trainable params: 1,124,201
Non-trainable params: 0

```

Figure 3.12: Model Architecture for Prediction using LSTM

An effective LSTM model was used to determine the battery's SOH, and the result is illustrated in Fig. 3.13. According to the figure, The LSTM approach tries to approximate the estimated SOH cycle to the real cycle of the battery failure condition as closely as possible.

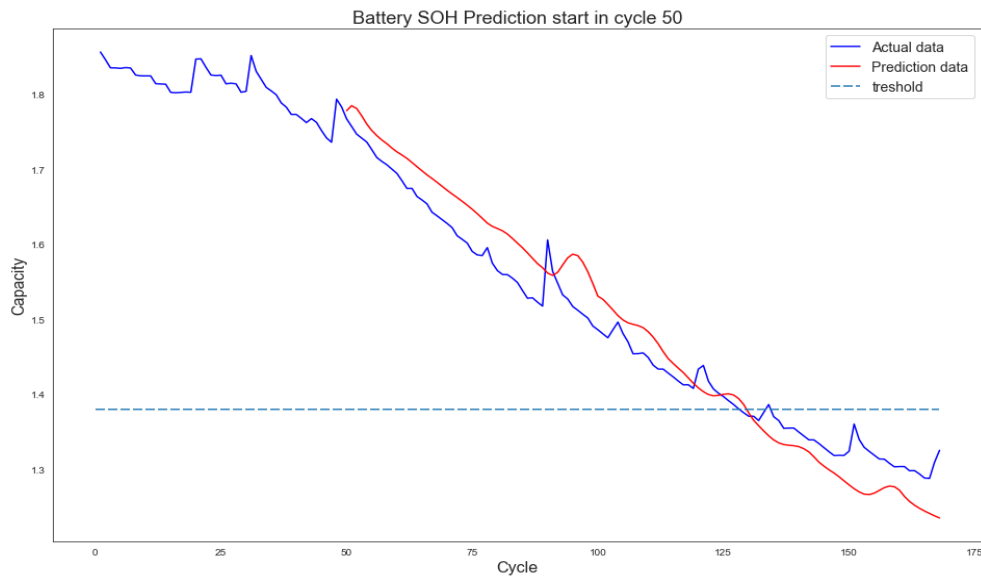


Figure 3.13: Battery RUL Prediction

The error is not always uniform and depends on the preceding forecast because the prediction SOH is based on the previously predicted SOH. Although the RUL error range varies if a similar learning framework is set up to operate at different times, the LSTM model executes significantly better compared to other kinds of learning algorithms. Finally, the graph shows that the capacity value and its behavior over time are very similar to the actual value and this result supports the data. The model's estimation of the RUL's error was 2 cycles, which leads us to believe that the model overestimated the battery's remaining life by 2 cycles.

The result in Table 3.1 shows 96% accuracy for the prediction of battery RUL with a Root Mean Square Error (RMSE) of about 0.040 along with an R Square value of about 0.912.

Table 3.1: RUL Accuracy

Technique	RMSE	R-Square
LSTM	0.040	0.912

Fig. 3.14 displays the variation in the error of a similar RUL forecast throughout various circumstances with a 2-cycle error deviation.

<p>The Actual fail at cycle number: 128 The prediction fail at cycle number: 130 The error of RUL= 2 Cycle(s)</p>

Figure 3.14: Error in RUL prediction

3.8 Conclusion

In this chapter, the data collection process and LSTM methodology are discussed. It provides a comprehensive framework for predicting the RUL of batteries. This architecture contains three stages that are pre-processing of the data, training of the data, and testing the dataset. After that, the resulting dataset is utilized to train an LSTM model using a sequence-to-sequence technique, in which the model is given a series of input data and forecasts the SOH at each instant in the sequence. The developed model can precisely forecast the RUL of different batteries, giving helpful details on battery performance and management. The result shows 96% accuracy for the prediction of battery RUL with a Root Mean Square Error (RMSE) of about 0.040 along with an R Square value of about 0.912.

CHAPTER 4

HARDWARE IMPLEMENTATION

4.1 Introduction

Batteries are essential components of electrical devices. Batteries are widely employed in a range of applications, such as electric-hybrid vehicles, electric automobiles (EVs), and electrical appliances because of their numerous benefits of sustainable characteristics, high density of power, minimal self-discharge level, and prolonged lifespans. However, in applications involving electric storage systems, batteries need to be handled with special attention. The aging procedure of the batteries is significantly increased by inadequate processes, especially over-current, over-voltage, or over-charging/discharging, which also raises the possibility of fire or explosion. Therefore, it is crucial to properly monitor and predict the battery's estimated useful life because an inaccurate capacity estimate might result in overcharging or over-degradation, which could irreversibly harm the battery.

It is well-known that these operations must be handled carefully to prevent over-degradation or over-charging, which may seriously harm the battery pack permanently or severely damage its ability to be repaired. As a result, an effective battery Forecasting and Monitoring System is crucial for assuring protection, prolonging the battery's efficiency, and minimizing the cost and reliability of the system. To track this project in real-time. The proposed block diagram is shown in the Figure 4.1.

4.2 Block Diagram

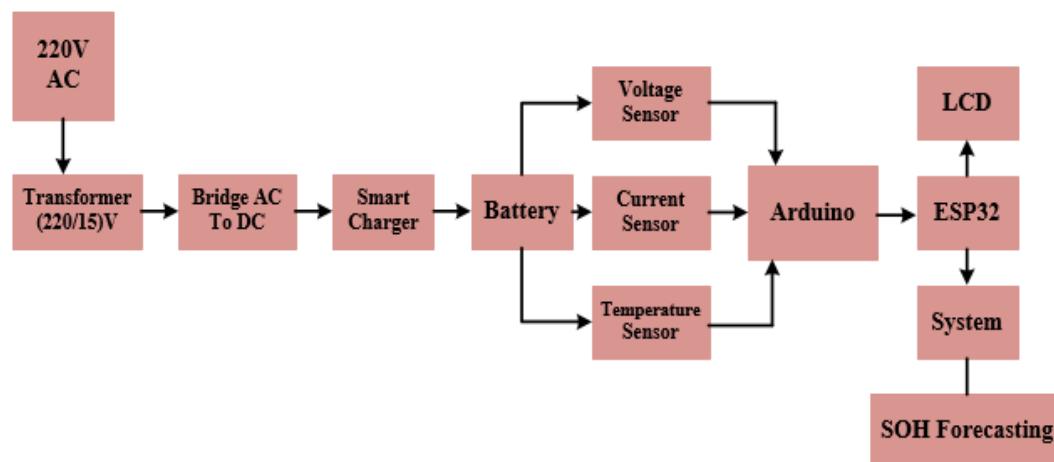


Figure 4.1: Block Diagram of Forecasting of Battery Lifespan and Monitoring System

4.3 List of Components

The following is a list of the equipment displayed in Table 4.1 below:

Table 4.1: List of equipment

Sr. No	Equipment's	Quantity
1	Transformer	1
2	Bridge AC To DC	1
3	Smart Battery Charger	1
4	Battery	1
5	Sensors(Current, Voltage, Temp)	3
6	Arduino	1
7	Esp32	1
8	LCD	1

4.3.1 Transformer

A transformer type known as a step-down transformer reduces the voltage from the primary side to the secondary side. In many different real-world applications, step-down transformers can be used. Step-down transformers have fewer secondary windings than primary windings in order to reduce the voltage absorbed as input by the primary coils. Here, the primary coil is attached to the input voltage source, while the secondary coil is wired to the load or device that requires a lower voltage. Simply dividing the total number of turns of the primary coil (N_p) with the total number of turns of the secondary coil (N_s), we may get the voltage transformation ratio of a transformer. In the project, we utilized a step-down converter from 220V AC to 15V AC. It receives 220V from WAPDA and scales down the voltage for utilization in the circuit.

The turns ratio of the step-down transformer is given as:

$$\frac{V_s}{V_p} = \frac{N_s}{N_p} \quad (4.1)$$

Where:

V_S = Secondary side's voltage.

V_P = Main side voltage.

N_S = Secondary coil's turns

N_P = Primary coil's turns

When the turns ratio N_S/N_P in a step-down transformer is less than 1, the secondary side's voltage is lower than the primary side's. Step-down transformers are widely utilized in many different applications, including power distribution, electrical appliances, electronics, and more.

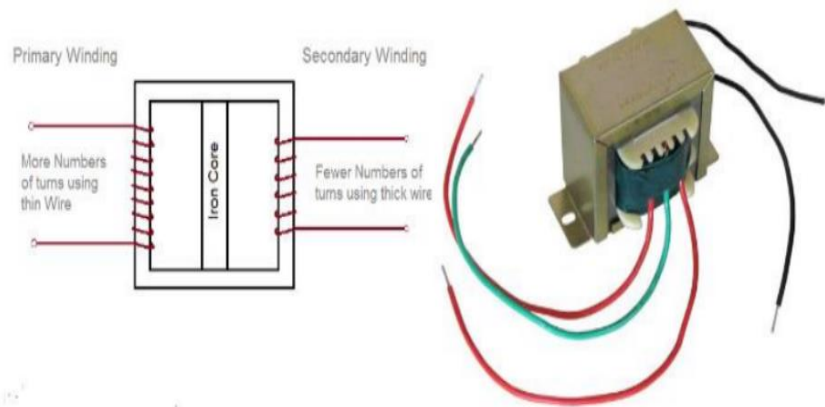


Figure 4.2: Step down transformer

4.3.2 Bridge Rectifier

A bridge rectifier is a circuit that converts alternating current (AC) to direct current (DC). It accomplishes this by directing the current only in one direction using four diodes. Two diodes are connected to either side of the AC input in a bridge configuration of the diodes.

The A terminal turns positive throughout the forward half cycle of any AC signals passed through the rectifier, while the B terminal turns negative throughout the reverse half cycle. As a result, D1 and D3 have a forward bias, while D2 and D4 have a reverse bias. Terminals B and A switch sides throughout the opposite (negative) half-cycle. As a result, diodes D1 and D3 demonstrate reverse bias conditions whereas diodes D2 and D4 demonstrate forward bias conditions. The circuit below illustrates the current flowing throughout the positive and negative cycles.

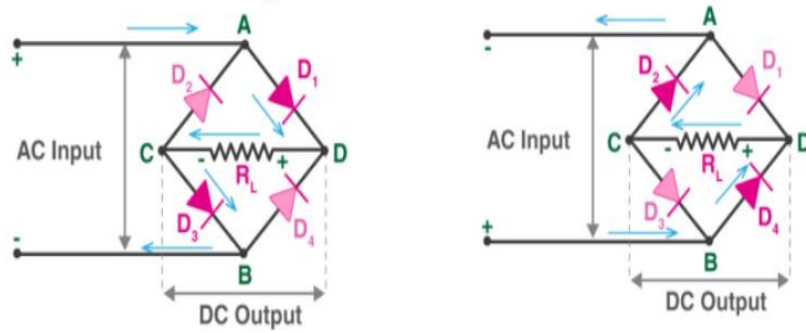


Figure 4.3: Circuit diagram of bridge rectifier

The flow of current through the overloading resistor R_L , displayed in the earlier diagrams, is equivalent to the positive as well as the negative half-cycles. The polarity of the DC signal that is produced can be either entirely positive or entirely negative. In the current scenario, the outcome is certainly positive. The input alternating current can therefore pass through a bridge rectifier throughout the positive as well as the negative half of the cycles. The output waveforms of the bridge rectifier are shown in the accompanying figure.

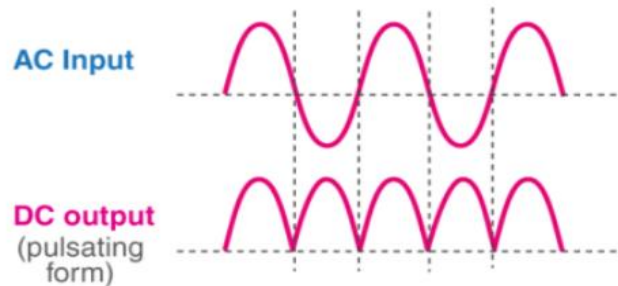


Figure 4.4: DC output (pulsating form)

A bridge rectifier's output is a pulsing DC voltage. The pulse's frequency is the same as the AC input's frequency. A capacitor can be attached to the bridge rectifier's output to smooth out the pulses. As a result, the DC output will be more uniform. In the circuit, 15V AC is obtained as output from the transformer which acts as input for the bridge rectifier. The bridge rectifier converts this AC to DC, and the resultant output voltage is 15 V DC.

4.3.3 Smart Battery Charger

A smart battery charger provides efficient and accurate charging for different kinds of batteries. These chargers use advanced charging algorithms and modern microprocessors that optimize the charging operation based on the battery's condition, chemistry, and voltage needs. To maintain a safe and

efficient charging rate, they continuously monitor the battery's condition and adjust the charging, voltage, and current accordingly. To avoid battery overcharging, the charge controller effectively acts as a voltage and current limiter. It controls the bridge rectifier's output voltage and the current flowing to the battery. When the battery is used heavily, the charge controller also influences how the battery charges. Here, the output of the bridge rectifier (14V) is the input of the battery charger. The input voltage range of this smart battery charger is 12V to 24V. It regulates the voltage and gives it to the battery for charging. The figure of the smart battery charger is given below in Fig. 4.5.



Figure 4.5: Smart battery charger

4.3.4 Battery

A device termed a battery is one that can store energy and then discharge it by converting chemical energy into electricity. A certain kind of battery and the size of the battery both affect how much energy can be stored in them. Batteries are essential for improving energy efficiency, lowering environmental impact, and providing secure power backup in a several scenarios, including UPS, smart power systems, and electric automobiles (EVs). Here, 12V Supreme 4 rechargeable battery is used to store energy given by a smart battery charger. It features a 3Ah capacity and a 12V rated voltage. Thus, in this project, the rectified voltage regulates with a smart battery charger and gives to the battery for charging. The battery uses this voltage to charge and supply energy to the load. In this project, the battery plays a significant part in determining the various parameters of the battery and forecasting the SOH. This system basically protects our battery by forecasting the SOH and displays different parameters on the LCD. The figure of the battery is given below in Fig. 4.6.



Figure 4.6: DC battery

4.3.5 Sensor

Current Sensor

A current sensor's purpose is to determine the electrical current that is passing through a conductor or circuit. In many applications where precise measurement, management, and safety of electrical currents are critical, current sensors play a vital role. They support effective power management, system improvement, and improved electrical system protection.

In the project, ACS712 current sensor is utilized with a rated current of 20A. Typically, the sensor's output voltage is centered at $VCC/2$ and has a sensitivity of 100 mV/A. The ACS712 sensor must first be powered within the demonstrated operating range of about 5V in order to be used. The analog-to-digital converter (ADC) within a microcontroller can be utilized to acquire the output of a sensor voltage. To enable precise measurement of the system's current, the positive connection of the 12V battery is linked to the ACS712 sensor's VCC pin, and the negative terminal is linked to the ACS712 sensor's GND pin and the Arduino Uno's GND pin. Here, the analog input pins of the Arduino Uno A0 connect to the OUT pin of the ACS712 sensor. The Hall effect principle is utilized by the ACS712 sensors in this project to measure current. The magnetic field produced by the conductor's current is detected by the Hall effect sensor, which then transforms it into an electric signal. This measurement is in analog form, which is first converted to digital values using an Arduino module and then display on LCD.

Voltage Sensor

An instrument that gauges the voltage in a circuit of electricity is termed a voltage sensor. Voltage sensors may detect voltage in a variety of different ways, including detecting low current levels and

high voltages. Numerous applications, such as power systems and industrial controls, depend on these devices. In the project, we employ a resistive voltage divider-based voltage sensor module, which has a sensing range of 0–25 DC voltages. The Voltage Sensor Module is a basic but beneficial module that decreases an input voltage by a factor of five using a potential divider.

The five pins on a voltage sensor are typically labeled Positive, Negative, VCC, GND, and OUT. For the sensor connection, attach the battery's negative terminal with the GND line of the voltage sensor and the 12V battery's positive terminal to the VCC pin. Attach the output pin of the voltage sensor to the Arduino Uno's analog input pin A1, and connect the voltage sensor's positive wire to the Uno's 5V pin and its negative wire to the Uno's GND pin. In this configuration, the voltage sensor continuously measures the battery voltage. It transmits that information to the controller, which then displays the voltage reading on the LCD after receiving the data.

Temperature Sensor

A temperature sensor is an instrument that measures and detects heat and turns it into an electrical signal. In the modern era, the temperature sensor is an essential component. They enable us to regulate the temperature in our residences, places of business, and automobiles. They also assist us in keeping track of the temperature of medical equipment and industrial activities. Temperature sensors are crucial to our comfort and safety. VCC, GND, and OUT are the three pins of the DHT11 sensor. Here, connects the sensing device's VCC wire to the Arduino Uno's 5V pin and its GND wire with the Uno's GND pin, and it's OUT pin to the Arduino Uno's digital input/output pin D7. Also, make sure the connection of the temperature sensor with the battery. The temperature sensor continuously measures the exact temperature of the battery and the ESP module displays results on LCD.

4.3.6 Arduino Controller

The Arduino Uno is a microcontroller board that is freely available and built on the ATmega328P chip. Compared to other boards, like the Arduino Mega board, etc., it is simple to use. The electronics component known as the Arduino UNO is beneficial in different control circuits. There are six PWM pins and six analog pins among the 14 digital input/output pins, a USB layout, and an Atmega328 chip. It also enables communication through I2C, the Serial, and SPI interfaces. Table 4.2 displays the Arduino controller's specifications.

Table 4.2: Specification of Arduino

Sr.No	Parameters	Specification
1	Microcontroller	ATmega328P
2	Input Voltage	5-12V
3	Flash Memory	32 KB
4	Crystal Oscillator	16MHz
5	Analog Pins	6 pins
6	Digital Pins	14 pins
7	Supply Voltage	5V

The Arduino Uno is utilized in the project to collect data from several sensors and measurements pertaining to the battery's operational circumstances. This includes gathering temperature, current, voltage, and other pertinent data.

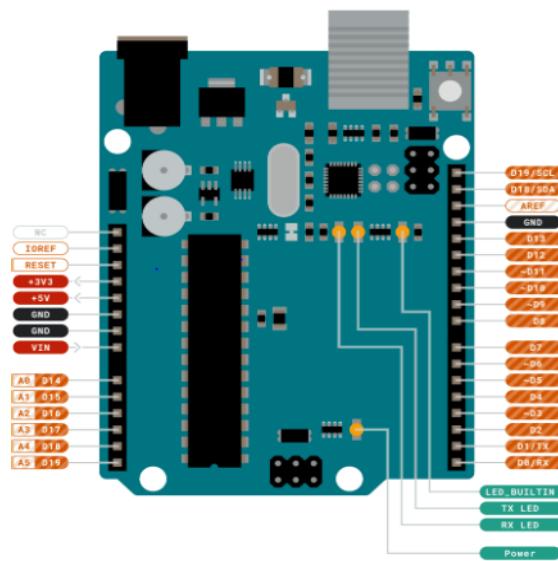


Figure 4.7: Arduino module

The SOH estimate algorithms require inputs, which the Arduino Uno provides through a sensor interface and periodic data retrieval. It processes the information acquired, performs calculations, and sends the current, voltage, temperature, and SOC data to the ESP module which shows these parameters on the LCD. This enables continuous monitoring of the battery's remaining useful life and feedback. In order to allow transmission of wireless data, the Arduino Uno is also integrated with

communication modules such as the ESP Wi-Fi module via serial communication. Figure below illustrate the Arduino module.

4.3.7 ESP32

The ESP32 is a well-known and influential microcontroller module that offers Bluetooth and Wi-Fi connectivity along with its processing capabilities. An essential TCP/IP connection is established via the affordable and user-friendly Wi-Fi module ESP32, which can easily be interfaced with microcontrollers through Serial Port. The basic feature of the module is shown in Table 4.3.

Table 4.3: ESP32 specification

Sr.No	Parameters	Specification
1	Input Voltage	7-12V
2	SRAM	64 KB
3	Operating Voltage	5V
4	Clock Speed	80MHz
5	Digital Pins	16
6	Analog Pins	1
7	Flash Memory	4MB

In the project, the ESP module is interfaced with the Arduino controller via serial communication referred to as UART communication in order to provide wireless data transmission and wirelessly monitor system performance. UART is a frequently used communication protocol since the majority of microcontrollers, such as the ESP32 and Arduino Uno, come with inbuilt UART hardware. UART offers bi-directional communication, allowing data to be sent and received simultaneously. This makes it possible for the ESP32 and Arduino Uno to exchange information and instructions in a two-way manner. Here, connect the ESP32 and Arduino Uno's GND (ground) pins for the UART connection. Additionally, the TX pin of the ESP32 should be connected to the RX pin of the Arduino Uno, and the RX pin of the ESP32 should be connected to the TX pin of the Arduino. This allows for the transmission of battery parameter data from the Arduino module to the ESP module. The LCD connected to the ESP module displays battery parameters including voltage, current, temperature, and SOC. Additionally, the ESP module wirelessly transfers battery parameter data to the system, which

creates a CSV file of battery data and displays real-time battery data analysis on the LCD. The LSTM algorithm is then applied to the CSV file data to forecast battery SOH.

4.4 Prototype Implementation

The prototype of the Forecasting of battery lifespan and Monitoring System using artificial intelligence (AI) is given below.

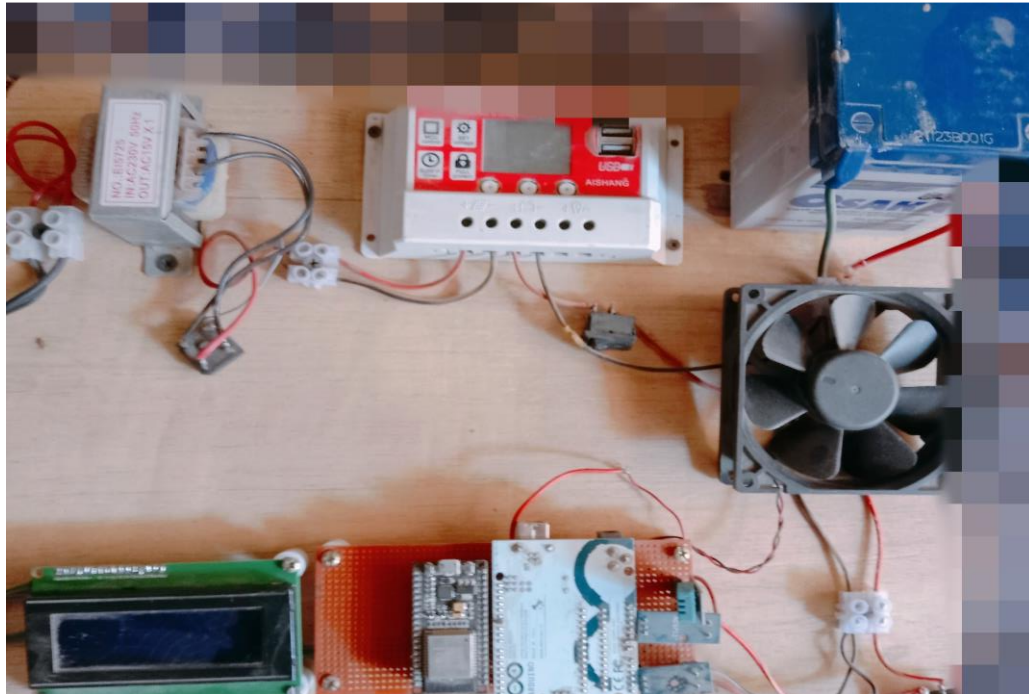


Figure 4.8: Prototype of forecasting of battery lifespan and monitoring system

4.5 Hardware Results

Fig. 4.8 shows the capacity degradation over the cycle of the battery which has a 3Ah capacity rating. It demonstrates how the battery's capacity and its age or cycle life relate to one another. The battery's capacity decline is shown by the slope of the degradation curve. The SOH of the battery may be predicted using this trend analysis, which helps in understanding the rate and behavior of degradation.

If the capacity degradation reaches a certain threshold as shown in the curve, it implies that the battery's useful life is about its end. The prediction of the battery's state of health (SOH) in relation to battery cycles is shown in Fig. 4.9. Based on actual and predicted degradation trends, SOH is forecasted.

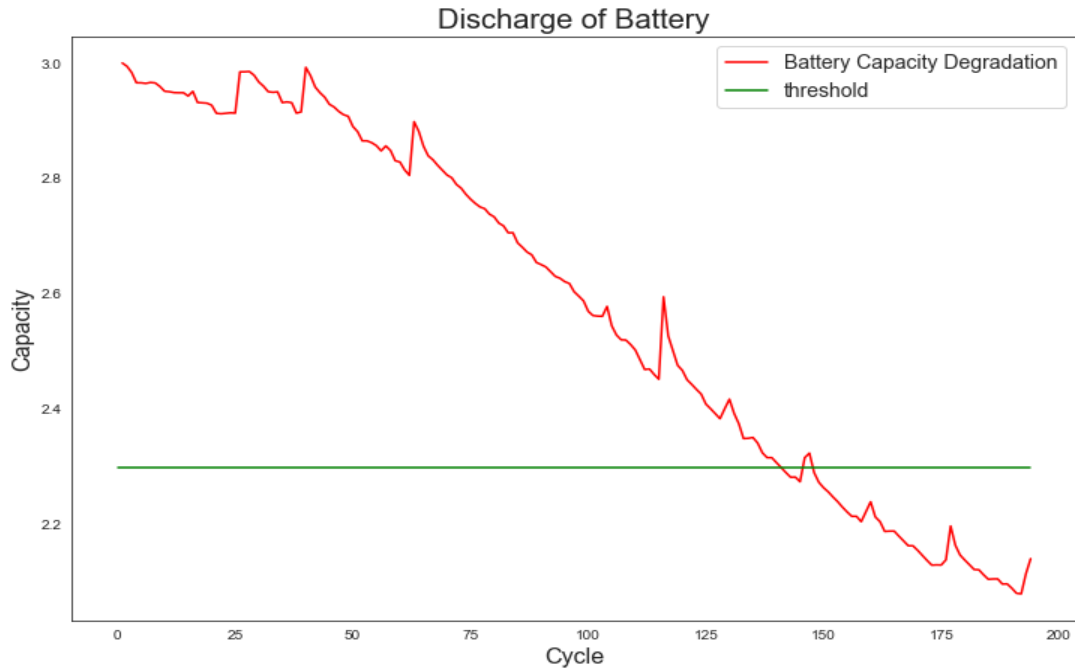


Figure 4.9: Capacity degradation curve

The forecasted curve shows the predicted degradation of the battery pattern generated by the estimation of the LSTM model, whereas the actual degradation curve depicts the observed decay of the battery over time.

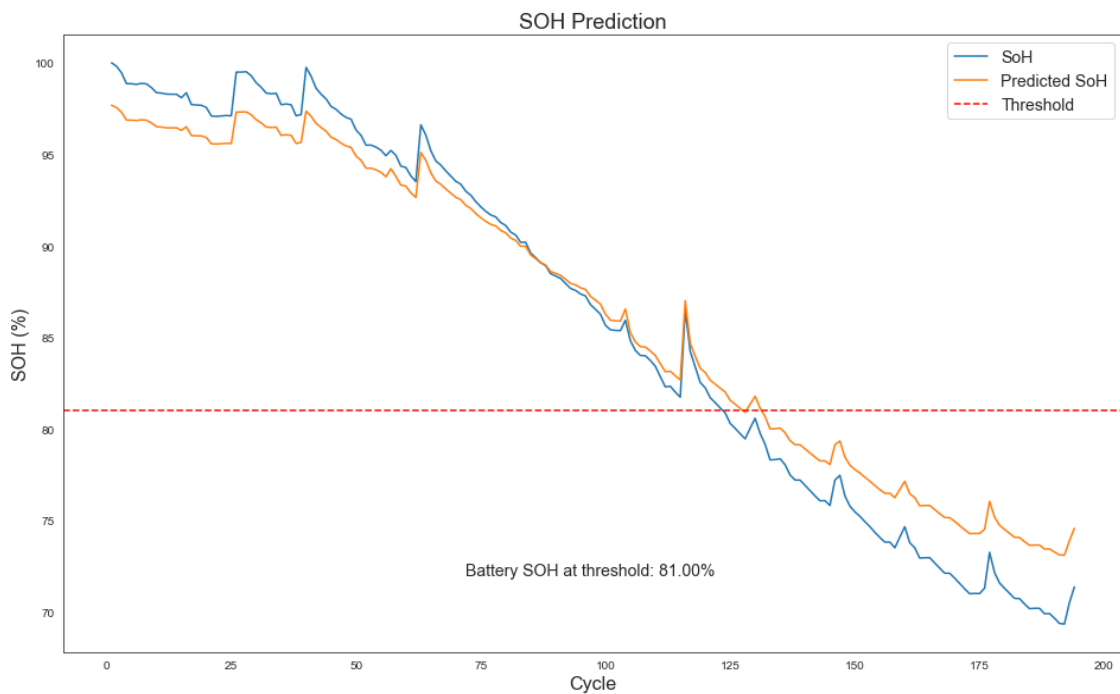


Figure 4.10: SOH Forecasting

By analyzing the actual and predicted curves, it is clear that the predicted value is extremely close to the real value over time for forecasting battery lifespan as shown in Fig 4.10. By comparing both curves the result illustrates a 97.6% accuracy for battery SOH prediction with a Root Mean Square Error (RMSE) of about 0.024 along with R Square value of about 0.965. Typically, the RUL estimate is determined by tracking the point on the predicted curve where it meets the predetermined threshold.

4.6 Conclusion

This chapter discusses the hardware implementation of the project and the different components used in prototype implementation with their specification. Basically, the Arduino Uno is utilized to collect data from different sensors. It processes the information acquired, performs calculations, and sends the battery parameters data to the ESP module that displays these parameters on the LCD. Here, the ESP module is interfaced with the Arduino controller via serial communication UART to wirelessly transmit battery parameters data to the system, which displays real-time battery data on the LCD and makes a CSV file. The CSV file data is then used for the forecasting of battery SOH using the LSTM approach. The results describe the real-time capacity degradation over the cycle and the implemented battery's lifespan (SOH) curves. The result illustrates a 97.6% accuracy for battery SOH prediction with a Root Mean Square Error (RMSE) of about 0.024 along with R Square value of about 0.965.

CHAPTER 5

BUSINESS DESCRIPTION

5.1 Form of Business

Our business will be a private business.

5.1.1 Team/Organizational Structure

Every business begins at a small scale and eventually begins to expand. Similarly, we will launch our company on a limited scale by producing fewer products and attempting to sell them all within a set time period. Our team members will run the business by cooperating with each other. The positions that will be given to the company member are listed below:

- Adnan Amin will be the CEO and Director of the company.
- Muhammad Tayyab Mushtaq will be the head of accounts and marketing.

5.1.2 Vision

Our vision is to promote the forecasting of battery lifespan and monitoring systems using Artificial Intelligence to provide accurate and reliable information about the health and functioning of batteries. The system accurately assesses the battery's health by monitoring and evaluating a variety of battery parameters in various electrical applications, which reduces maintenance costs, extends battery life, and maximizes business utilization. Our goal is to lower the overall cost of battery ownership while also monitoring and forecasting SOH for Pakistani enterprises. The industrial revolution will arrive in Pakistan because of the implementation of this project for the first time.

5.1.3 Mission

Our mission is to provide Pakistani firms with innovative SOH forecasting and battery monitoring solutions so they can maximize the effectiveness, durability, and cost-effectiveness of their battery assets. We work to improve operating efficiency, decrease downtime, and maximize the return on battery investments through precise health assessment, predictive maintenance, and efficient resource allocation. Our LSTM insights and practical suggestions aim to assist Pakistani companies in making wise decisions, lowering maintenance expenses, and promoting sustainable growth in the energy storage industry.

5.1.4 Goal and Objectives

Our major goal is to improve the performance, lifespan, and cost-effectiveness of battery assets through accurate health assessment, predictive maintenance, and efficient resource allocation. Our objective is to provide real-time monitoring and analysis of battery performance to assist businesses make knowledgeable decisions about the deployment and utilization of batteries. We also aim to lower the overall cost of battery ownership by minimizing unplanned downtime, preventing premature battery replacements, and optimizing maintenance schedules based on the health and performance data provided by the monitoring system. Similarly, to prevent the battery from malfunctioning and to enhance charging and discharging processes is our goal.

5.2 Industry and Marketing Analysis

5.2.1 Industry Analysis

After the industrial visits, we came to know the availability of this product and idea in the Pakistani market was not much familiar to most of the industry and no industry is currently working on this project. Our product is unique to the Pakistani industry and that is the major benefit that if we can get this product recognized we will be the first one in the market to launch a new Artificial Intelligence base battery SOH forecasting and monitoring system. However, due to rising energy demands, the integration of renewable energy sources, and a focus on sustainable power solutions, the energy storage business in Pakistan has been expanding significantly.

Through market and industry research, we learned that the demand for battery storage systems has grown because of the growing utilization of energy from renewable sources like wind and the sun energy to store excess power produced during peak hours and deliver it during low-demand or non-generating periods. After doing inspections and assessments, we found a lot about the areas where our project lags and the specific components that need to be addressed to progress it as an economically viable organization.

5.2.2 Competitive Analysis

As we have discussed that many companies are working on this product worldwide but not in Pakistan. Advanced energy storage systems with built-in monitoring and control features for efficient battery management are offered by Tesla Energy, ABB, and NEC Energy systems. These companies are very much in this market but we use a different technique to complete this product so we are at the top of

the list. This experiment is not much done by our industries so we should avail of this opportunity and have to fulfill the requirements of the market. With continued growth, to serve the people and Industries, the company will provide easy and cost-effective services to the companies of Pakistan and all others which are existing on the globe.

Our purpose is to develop a product that has the following benefits to other products:

- It forecasts the SOH of the battery using the modern LSTM approach.
- It monitors the aging and charging status of the battery.

5.3 SWOT Analysis

5.3.1 Strengths

- SOH forecasting using advanced technology
- An all-encompassing solution to determining battery health, improving performance, and prolonging battery life.
- Product customization and scalability.
- Less maintenance requirement
- Low running cost

5.3.2 Weaknesses

- Lack of awareness among consumers about the value and advantages of SOH forecasting and battery monitoring systems.
- Initial challenges in execution.

5.3.3 Opportunities

- The growing demand for energy storage solutions over a range of industries.
- The audience will be attracted by AI-based technologies.
- Supportive government policies and promoting energy storage and renewable energy in Pakistan provide an opportunity for the product to get popularity and market acceptance.

5.3.4 Threats

- Rapid development in battery technology and monitoring systems may result in the release of new, disruptive products that might threaten the product's market position.

- Since both established firms and new competitors provide similar solutions, fierce competition in the market poses a threat.

5.3.5 Marketing Objectives Follow

- Today, social media is a tremendously powerful, effective, and affordable source of advertising.
- The news channel on electronic media is also a very popular and convincing source for promoting our product.
- For the advertising of our project, we will specifically target the EV industry, power storage system industry, and solar businesses.
- Ensuring the government about the product, its requirements, and its benefits.

5.4 Marketing Communication

To promote a business model and create awareness of our products or services, marketing communication is essential. To reach the target audience, it includes using strategic messages and a variety of communication channels. Social and electronic media are considered the most powerful and effective sources of promotion and advertisement. Our businesses can efficiently reach their target audience, increase brand awareness, encourage customer involvement, and eventually accomplish our business goals by combining various marketing communication types.

5.4.1 Advertising

Advertising is the paid marketing of products or services through a variety of media, including print, radio, television, outdoor billboards, web banners, and sponsored content. It aims to reach a large audience to raise awareness, create interest, and increase sales. Advertising is one of the most commonly used marketing tactics in which the information about the goods and services of the business can be effectively conveyed to the vast target audience.

5.4.2 Public Relations

Public relations aims to create and preserve a positive public perception of the company's idea through media coverage, press releases, events, and connections with journalists and influencers. It tries to increase brand visibility, credibility, and reputation.

5.4.3 Digital Marketing

To reach and engage customers, digital marketing uses a variety of online tactics for our product promotion. To make websites more visible, this comprises email marketing, influencer marketing, pay-per-click (PPC) advertising, search engine optimization (SEO), social media marketing, and online PR activities.

5.4.4 Social Media Marketing

Through websites like Facebook, Twitter, Instagram, LinkedIn, and YouTube, social media marketing connects and interacts with the target audience to promote our product. Order to increase awareness of the company and customer loyalty involves creating appealing content, running sponsored advertisements, and developing conversations.

5.4.5 Direct Marketing

Direct marketing is contacting potential clients directly through means including direct mail, telemarketing, SMS marketing, and customized email campaigns. It tries to increase revenue, foster customer relationships, and generate leads.

5.4.6 Personal Selling

Marketing involves the selling of our project through videos and portals. Telling our customers how our system can fulfill their needs and how this bus can help them in making their work easier, convenient, and more economical.

5.5 Financial Plan

5.5.1 Resources Required

- To begin a business, all necessary resources must be available. (For example, machinery, test equipment, and electronic equipment)
- Legal requirements, and a physical location.
- Technology Infrastructure
- Capital
- Electricity
- Human Resources.

Table 5.1 illustrates the initial cost budget of the forecasting of battery lifespan and monitoring system project.

Table 5.1: Initial Cost Budget

Sr. No	Description	No. Of Units	Cost per Unit (Rs.)	Amount (Rs.)
1	PC/Laptop	1	50,000.00	50,000.00
2	Internet	--	3,000.00/month	36,000.00
3	Electricity	--	10,000.00/month	120,000.00
4	Generator	1	150,000.00	150,000.00
5	Furniture and Fixture	--	40,000.00	40,000.00
6	Office Rent	--	15,000.00	180,000.00
7	Digital Marketing (SEO/SMOs)	3 months	25,000.00	75,000.00
8	Printer	1	17,000.00	17,000.00
9	Legal Expenses	--	25,000.00	25,000.00
10	Research and Development	6 months	10,000.00	60,000.00
11	Miscellaneous	--	5,000.00	10,000.00
12	Raw Material	10	14,000.00	140,000.00
	Total			903,000.00

Table 5.2 represents the statement of comprehensive budget of the project.

Table 5.2: Statement of Comprehensive budget

Sr.No	Description	1st Year	2nd Year	3rd Year	4th Year	5th Year
1.	Revenue	360000/-	450000/-	540000/-	675000/-	900000/-
2.	Cost of Production	160000	200000	240000	300000	400000

3.	Other Operating Expenses	110000	115000	122000	135000	152000
4.	Depreciation	9000	9000	9000	9000	9000
5.	Miscellaneous	6000	7000	5000	8000	10000
6.	Marketing Expenses	10000	13000	15000	12000	16000
7.	Profit Before Commission	65000/-	106000/-	149000/-	211000/-	313000/-
8.	Commission	14100	20300	26000	51250	110700
9.	Profit After Commission	50900/-	85700/-	123000/-	159750/-	202300/-

5.6 Notes

5.6.1 Note-1

All costs and income are based on estimates.

5.6.2 Note-2

The straight-line technique is used to depreciate every non-current asset at 10% annually.

5.6.3 Note-3

A 10% commission will be paid on annual profit.

5.6.4 Note-4

According to the "Income Tax Ordinance, 2001," the income is below the minimum prescribed level every year. Therefore, no tax obligation was identified.

5.6.5 Note-5

The required raw materials used in the production include sensors, Arduino, relays, Wi-Fi controllers, and other electrical components.

5.6.6 Note-6

Electricity is an example of a variable overhead that changes depending on production, units generated over time, etc.

5.6.7 Note-7

The calculations are based on assumptions, so there is a chance that they may be imparity.

5.7 Conclusion

In this chapter, the company model was thoroughly analyzed and examined for the forecasting of battery lifespan and monitoring systems. Additionally, the chapter has delved into the competitive environment, market analysis, marketing communication strategies, and SWOT analysis. Moreover, the identification of customer segments and understanding their needs and preferences is vital for tailoring the business model to deliver value and generate revenue. This chapter described the complete business plan along with the five-year financial plan.

CHAPTER 6

CONCLUSION AND FUTURE WORK

6.1 Conclusion

In the thesis, our main goal was to develop a battery state-of-health (SOH) forecasting and monitoring system utilizing AI, especially the Long Short-Term Memory (LSTM) algorithm. The objective was to provide an accurate and reliable method for predicting the SOH and degradation of batteries over time, allowing for proactive maintenance and efficient utilization of battery resources.

First, we presented a brief overview of the project, emphasizing the value of accurate forecasting and battery health monitoring systems. We also discussed that inappropriate processes, including over-voltage, over-current, or over-charging/discharging, significantly increase the degradation of the batteries and potentially increase the risk of fire or explosion. Therefore, it's crucial to carefully monitor and analyze the battery's remaining life because an inaccurate capacity estimate might result in overcharging or over-discharging, which may damage the battery permanently. We also outlined the objectives and scope of the study.

Then, we presented an extensive literature review that addressed the most recent studies and technological advancements in the field of battery SOH monitoring and forecasting. We talked about a variety of methods and algorithms applied in this field, including LSTM and machine learning techniques. This chapter laid a strong basis for our project and revealed areas for further research as well as the potential for improvement.

In the thesis, we described the data collection and methodology employed in the project. We explained the process of acquiring battery data, including relevant parameters and measurements. Additionally, discussed a comprehensive framework for predicting the RUL of batteries. Data initial processing, data training, and data validation are the three processes that compose this methodology. The resulting dataset is then used to train an LSTM model using a sequence-to-sequence approach, where the model was fed a sequence of input data and predicted the RUL. The developed model can precisely forecast the RUL of batteries, providing valuable insights into battery performance and maintenance. Here, presented details on the methodology and procedures used in our project.

In the end, focused on the hardware implementation of the forecasting of battery lifespan and monitoring system. We presented the hardware components used, their interconnections, and the

overall architecture of the project. Additionally, we discussed the configuration of the LSTM architecture into the hardware setup, enabling real-time predictions and monitoring. Here, the Arduino Uno is utilized to collect data from different sensors and performs calculations, and send the battery parameters data to the ESP module that displays these parameters on the LCD. The ESP module is interfaced with the Arduino controller via serial communication UART to wirelessly transmit battery parameters data to make a CSV file. The CSV file data is then used for the forecasting of battery SOH using the LSTM approach. The results describe the real-time capacity degradation over the cycle and the implemented SOH curve over the cycle.

In conclusion, the thesis presented a comprehensive analysis of the implementation of a battery SOH forecasting and monitoring system deploying the LSTM algorithm. The LSTM model was successfully integrated into the hardware configuration for real-time predictions, enabling proactive maintenance and optimizing battery consumption. Our project demonstrated how the LSTM algorithm is superior to conventional statistical techniques in terms of accuracy and dependability. The research advances the field of battery health monitoring and forecasting, enabling better resource and maintenance management techniques.

6.2 Future Work

The thesis presents a solid foundation for further research and innovation in the domain of forecasting battery health and monitoring system. By enhancing battery performance, longevity, and overall dependability, the developed technology has the potential to positively affect a number of fields, including electric cars, renewable energy systems, and portable electronic devices. Further improvements may be made to the battery SOH forecasting and monitoring system to improve its reliability, accuracy, flexibility, and economic feasibility.

Even though this project achieved key milestones, there are still opportunities for improvement. Extending the dataset, investigating new characteristics, improving the LSTM model, and integrating the monitoring system with BMS should be the main goals of future studies. Some of the prospective areas for future research are outlined in the following points:

1. **Enhanced Model Architecture:** Data temporal dependencies may be effectively captured using the LSTM technique. However, investigating additional modern deep learning architectures, including transformer-based models or convolutional neural networks (CNNs),

may result in significant increases in predicting accuracy. A promising area for future study might be comparing various model designs and investigating ensemble techniques.

2. **Feature engineering and Selection:** The model's performance might be improved by looking at feature selection methods and choosing the most crucial battery parameters for forecasting SOH. Additionally, investigating feature engineering techniques like time-series transformations or domain-specific feature extraction may offer insightful information on how batteries degrade.
3. **Online Learning and Adaptive Models:** An interesting topic for future research is the ability to modify and update the LSTM model in real-time when new battery data becomes available. The implementation of learning online strategies that can continuously modify the model parameters and respond to changing battery conditions would be beneficial for long-term monitoring and maintenance.
4. **Integration with Decision Support Systems:** By integrating the battery SOH forecasting and monitoring system with decision support systems, automated decisions based on the anticipated battery health would be possible. The utilization and lifetime of battery systems might be increased by creating decision rules, maintenance plans, and optimization algorithms that consider the predicted SOH.
5. **Real-World Validation:** Extensive field testing and validation studies using a variety of battery systems and operating scenarios would offer insightful real-world information on the functionality and generalizability of the created system. Working together with industry partners or putting the system into use would help confirm its efficiency and reveal any practical issues that need to be resolved.
6. **Cost Analysis and Economic Viability:** Evaluating the battery SOH forecasting and monitoring system's cost-effectiveness and economic viability is a crucial factor to take into account. The adoption of the system would be more justified if a thorough cost analysis was conducted that took into account the advantages of proactive maintenance, less downtime, and optimized battery consumption. This study would also shed light on the system's economic effect.

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