



Artificial Neural Network based Battery Management System on
State of Charge Estimation for Optimal Operation of Photovoltaic-
Battery Integrated System

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Artificial Neural Network based Battery Management System on State of Charge Estimation for Optimal Operation of Photovoltaic-Battery Integrated System

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DECLARATION

I declare that the work in this thesis was carried out in accordance with the regulations of Universiti Malaysia Sarawak. Except where due acknowledgements have been made, the work is that of the author alone. The thesis has not been accepted for any degree and is not concurrently submitted in candidature of any other degree.



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ABSTRACT

Due to the reduction of fossil-fuel utilization PV-Battery integrated system is a preferable power supply in many areas of the world. Designing a supervisory controller that can harvest high energy density and prolong the battery lifetime is one of the major challenges in a battery energy storage system. A proper Battery Management System (BMS) monitors the battery charge status and takes decision to lengthen the battery lifetime. A regulatory State of Charge (SOC) estimation based on PV-Battery standalone system is presented in this research that significantly addresses the issues. The proposed control algorithm estimates SOC by Backpropagation Neural Network (BPNN) scheme and implements Maximum Power Point Tracking (MPPT) system of the solar panels to take decision for charging, discharging or islanding mode of the Lead-Acid battery bank. The proposed model is designed in MATLAB/SIMULINK software and the experimental prototype is assessed via dSPACE 1104 component. The proposed power control strategy is explored as robust as well as attained the effective objective of standalone PV-Battery Management System e.g. avoiding overcharging and deep-discharging manoeuvre under different solar radiations and temperatures. A case study is presented for several SOC estimation methodologies that demonstrate the effectiveness of the proposed strategy with 0.082% error.

Keywords: Battery Management System (BMS), State of Charge (SOC) Estimation, Backpropagation Neural Network (BPNN), PV-Battery system

Sistem Pengurusan Bateri Berasaskan Rangkaian Neural Buatan Menggunakan Anggaran Keadaan Caj Untuk Operasi Optimum Sistem Bateri Fotovoltaik Bersepadu

ABSTRAK

Pengurangan penggunaan bahan bakar fosil menjadikan sistem bersepadu PV-Bateri sebagai bekalan kuasa yang lebih disukai di seluruh dunia. Perancangan dari segi penyeliaan adalah salah satu cabaran utama dalam sistem penyimpanan tenaga bateri bagi mendapatkan ketumpatan tenaga yang tinggi dan memanjangkan jangka hayat bateri. Sistem Pengurusan Bateri yang betul (BMS) boleh memantau tahap status caj bateri dan sekaligus boleh memanjangkan jangka hayat bateri. Sistem pengawalan PV-Bateri yang diasaskan daripada anggaran penyata caj (SOC) telah dibentangkan dalam kajian ini yang secara optimal bagi menangani isu-isu tersebut. Algoritma kawalan penganggaran SOC daripada Skema rangkaian Neural Network (BPNN) dan pelaksanaan sistem Penjejakan Titik Maksimum (MPPT) bagi panel solar merupakan keputusan yang diambil untuk mengecas, menggunakan atau memakai mod bank bateri Lead-Acid. Model yang dicadangkan ini direka bentuk dalam perisian MATLAB / SIMULINK dan prototaip eksperimen ini dinilai melalui komponen dSPACE 1104. Eksplorasi kajian ini mendedahkan bahawa strategi kawalan kuasa yang dicadangkan adalah kukuh dan memenuhi pelbagai objektif Sistem Pengurusan Bateri PV seperti mengelakkan berlakunya pengecasan berlebihan dan cara penggunaan yang jauh di bawah radiasi dan suhu solar. Satu kajian kes telah menunjukkan keberkesanan (Ralat 0.082%) strategi dengan jayanya melalui beberapa penggunaan metodologi anggaran SOC.

Kata kunci: *Sistem Pengurusan Bateri (BMS), Anggaran Penyata Caj (SOC), Skema Rangkaian Neural Network (BPNN), Sistem PV-Bateri*

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LIST OF ABBREVIATIONS

AAE	Average Absolute Error
AAPE	Average Absolute Percentage Error
AEKF	Adaptive Extended Kalman Filter
AGA	Adaptive Genetic Algorithm
Ah	Ampere-hour
AHIF	Adaptive H-Infinity Filter
ANFIS	Adaptive Neuro-Fuzzy Inference System
ARX	Auto Regressive Exogenous
BECM	Battery Equivalent Circuit Model
BESS	Battery Energy Storage System
BJDST	Beijing Dynamic Stress Test
BMS	Battery Management System
BPNN	Back Propagation Neural Network
BSA	Backtracking Search Algorithm
CARMA	Controlled Auto-Regressive and Moving Average
CCD	Constant Current Discharge
CPE	Constant Phase Element
DEIS	Dynamic Electrochemical Impedance Spectroscopy

DEKF	Dual Extended Kalman Filter
DP	Dual Polarization
DST	Dynamic Stress Test
DWRLS	Decoupled Weighted Recursive Least Squares
EIS	Electrochemical Impedance Spectroscopy
EKF	Extended Kalman Filter
ELM	Extreme Learning Machine
EMF	Electromotive Force
EoL	End of Life
FFFB	Feedforward-Feedback
FFRLS	Forgetting Factor Recursive Least Square
FNN	Fuzzy Neural Network
FUDS	Federal Urban Driving Schedule
GMEKF	Grey Extended Kalman Filter
GRNN	Generalized Regression Neural Network
H_{∞}	H infinity
HIF	H-Infinity Filter
HPPC	Hybrid Pulse Power Characterization
HWFET	Highway Fuel Economy Test

IARMA	Incremental Autoregressive and Moving Average
IIM	Invariant-Imbedding Method
LFP	LiFePO_4
LIB	Lithium Ion Battery
LMO-NMC	$\text{LiMn}_2\text{O}_4\text{-LiNi}_{1/3}\text{Mn}_{1/3}\text{Co}_{1/3}\text{O}_2$
LS	Least Squares
LSSVR	Least Square Support Vector Machine for Regression
LTO	Lithium Titanium Oxide, $\text{Li}_4\text{Ti}_5\text{O}_{12}$
MADS	Multiplies, Divides and Square Roots
MAE	Mean Absolute Error
MAFF	Multiple Adaptive Forgetting Factor
MAPE	Maximum Absolute Percentage Error
MmAE	Maximum Absolute Error
MPSO	Multi-Swarm Particle Swarm Optimization
NCA	$\text{LiNi}_{0.80}\text{Co}_{0.15}\text{Al}_{0.05}\text{O}_2$
NEDC	New European Driving Cycle
NMC	Nickel Cobalt Manganese Oxide LiNiMnCoO_2
OCV	Open Circuit Voltage
OLS	Orthogonal Least-Squares

ORP	Odd Random Phase
PDE	Partial Differential Equation
PNGV	Partnership for a New Generation of Vehicles
PSO	Particle Swarm Optimization
RBFNN	Radial Basis Function Neural Network
RBNN	Radial Basis Neural Network
RLS	Recursive Least Square
RQ	Rayleigh quotient
RSMO	Robust Sliding Mode Observer
RTLS	Recursive Total Least Squares
RUL	Remaining Useful Life
SC-ANFIS	Subtractive Clustering-ANFIS
SFFF-RLS	Single Fixed Forgetting Factor-Recursive Least Squares
SFNN	Stochastic Fuzzy Neural Network
SOC	State of Charge
SOF	State of Function
SOH	State of Health
SVR	Support Vector Machine for Regression
UDDS	Urban Dynamometer Driving Schedule

UKF	Unscented Kalman Filter
UOB	Oviedo Battery Laboratory
VFFRELS	Variable Forgetting Factor Recursive Extended Least Squares

CHAPTER 1

INTRODUCTION

1.1 Chapter Overview

This chapter lays down the foundation for the thesis and provides a brief introduction of Battery Management System based on State of Charge estimation control method for PV-Solar system. This study offers knowledge on ANN to improve the potentiality on battery storage section. To examine the algorithms and techniques of the study, this chapter provides with detail discussions on the background and motivation of the study in Section 1.2, whereas Section 1.3 addresses the introduction to the technology and schemes used by the study and overview of BMS.

Furthermore, Section 1.4 addresses the problem statement that discusses the current issues and problems in BMS. For which, hypothesis are elaborated in Section 1.5 while from such hypothesis several research questions appeared which are given in Section 1.6. Moreover, to address the research questions of this study there are objectives set in Section 1.7 whereas the contributions to the existing knowledge are given in Section 1.8. Section 1.9 and Section 1.10 represent the significance and scope of this research accordingly. Finally, the summary and thesis structure are provided at the end of this chapter in Section 1.11.

1.2 Background and Motivation

Solar photovoltaic (PV) power plants have emerged a possible option to satisfy our increasing energy condition and reduce the fossil fuels dependency. Developing countries need to make use of full potential of PV resources to meet the incremental demand of energy security. Though energy storage-less PV-diesel microgrid system with optimal operating

strategy can afford for continual power supply in the unelectrified rural area, it may not be an environmentally auspicious due to the reliance on fossil based fuels and total dispatched energy cost (Benjamin et al., 2019; Ghenai & Bettayeb, 2019).

Moreover, a standalone PV system is an inadequate source of electricity supplier because of power fluctuations created by varying solar radiation and atmospheric temperature. Hence, Maximum power point tracking (MPPT) is used commonly with PV solar systems to maximize power extraction from PV supply. The intention of MPPT is to make certain that, at any environmental situation, the maximum power is harvested from the PV panels by dint of matching its I–V working point with the corresponding power converter. Generally, a PV array operates along with a dc–dc power converter, whose duty cycle is accustomed to aptly track the MPP of the array (Gopi & Sreejith, 2018). Lasheen and Abdel-Salam (2018) presented an exhaustive literature review on offline and online techniques for PV MPPT system. Ishaque et al. (2014) evaluated the performance of perturb and observe (P&O) and incremental conductance (IC) MPPT technique on the basis of European Efficiency Test EN 50530 that was specially devised for the dynamic performance of PV system. Alik and Jusoh (2017) approached an improved P&O based MPPT algorithm for partial shading condition PV system through MATLAB/SIMULINK platform that performed zero ripple at the load side. Kamran et al. (2018) simulated a modified Perturb and Observe (P&O) MPPT algorithm in MATLAB/SIMULINK software that confines a search space of the power curve for 10% area. The proposed model contains Maximum Power Point (MPP) in this search space and starts perturbation and observation technique by lessening the response time with a solar tracker.

On the other hand, only PV modules cannot meet the load demand during cloudy day or night time. Thus, a Battery Management System (BMS) is mandatory to combine with a standalone PV system to provide power uninterruptedly throughout the day and night time (Ci et al., 2016; Yang et al., 2018). Generally, Lead-acid batteries have flat terminal voltage in the state of charge (SOC) range of about 40% to 80% as shown in Figure 1.1 and the batteries in PVs are normally operating in this SOC range (Lee et al., 2017). The voltage variation in this range is less than 0.45 V only. Such slight voltage differences can hardly be used to effectively persuade the proper charging and discharging processes and consequently, another essential part of apprehension is the control and power distribution in PV-Battery integrated system.

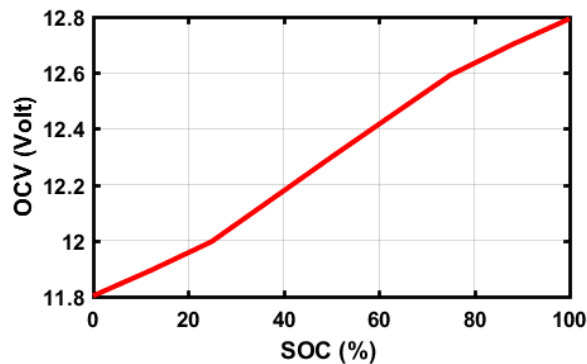


Figure 1.1: OCV vs SOC relationship for 12 V Lead-Acid battery status (Lee et al., 2017)

In the preceding, there have been various attempts to develop optimal and novel power control strategies for the PV-Battery hybrid system to maintain a continuous power supply for the load demand. Chong et al. (2016) proposed PV/Battery-Supercapacitor hybrid system to elongate the battery lifecycle by dropping the dynamic stress and peak current demand of the battery. Natsheh and Albarbar (2012) studied on grid connected 28.8 kW PV-Battery integrated system in MATLAB/SIMULINK software by implementing P&O MPPT technique. The system showed power deviation (1.7 kW) between model prediction

and actual power because of clouds, dust, snow cover and aging effect. Alramlawi et al. (2018) considered grid scheduled blackouts for optimal operation of PV-Battery hybrid system and calculated battery SOC to prolong the battery lifetime.

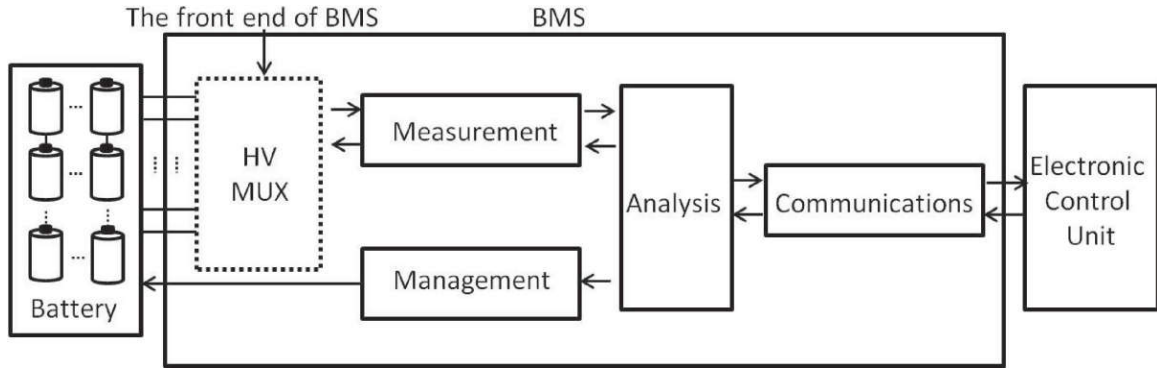


Figure 1.2: General model of BMS (Li et al., 2017)

Yu et al. (2018) constructed 2nd order Equivalent Circuit Model (ECM) of Valve Regulated Lead–Acid (VRLA) battery for Solar Home Systems and considered open circuit voltage (OCV) vs state of charge (SOC) non-linear relationship for low C-rate applications. Devarakonda and Hu (2014) introduced a fuzzy model to estimate SOC for Lead-Acid battery on behalf of Extended Kalman Filter (EKF) scheme. Cui et al. (2018) established lead-acid battery ECM for energy storage power station and estimated SOC by EKF method. However, there is no work done on proper control strategic for a standalone PV-storage integrated system by monitoring the battery charge status till now.

1.3 Battery Management System and its Application

BMS is a ploy that consists of hardware and software implementation of the battery. The general model of BMS is shown in Figure 1.2 (Li et al., 2017). This one is operated to lengthen the battery life, ensure its security and support the precision of different states approximation to maintain the energy sections impeccably (Yang et al., 2018). For this

reason, different types of topographies are employed to govern the states in several types of cells and battery packs. The BMS is not only the important element of a method but also goes through the SOC, State of Health (SOH), Remaining Useful Life (RUL) accuracy in the direction of touching the battery End of Life (EOL). There are three main objectives common to all BMSs such as:

- i. Protect the battery from damage.
- ii. Prolong the life of the battery.
- iii. Maintain the battery in the required states of the application for which it was specified.

1.4 Problem statement

Renewable energy resources definitely PV-Battery integrated system is the most momentous and cleanest energy generation in this modern period. Although the standalone systems are involved in some spaces of the world as a smart-grid section, the battery storage system has fallen down the entire potentiality of the structure owing to the scarcity of a proper control system (Morstyn et al., 2018). From numerous experimentation of researches, it has been perceived that only 80-90% to 20-40% battery charges can be executed from a battery cell (Dell et al., 2014; Devarakonda & Hu, 2015). Again, the cells do not carry the same amount of charges at every single time in the battery pack because of a few reasons i.e. temperature, aging effect, chemical reaction etc. At this moment particularly during charging-discharging period, without having a proper control system, the more charged battery becomes over-charge and less charged battery goes to Depth of Discharge (DOD). For this reason, the problematic statements are prepared as follows:

- i. Designation of a proper BMS is indispensable to monitor the PV-Battery integrated system in the direction of improving the battery performance.
- ii. SOC estimation accuracy for the engaged battery is mandatory to protect the storage system within its feasible workability.
- iii. The corroboration of the simulated model is imperative by dint of experimental setup caused by facilitating the industrial solicitation.

1.5 Hypothesis

The conventional PV-Battery integrated systems use the open circuit voltage to calculate the charge status of the battery bank. Though the OCV of the battery keeps relation with the SOC, it is quite difficult to protect the battery from damages without having an appropriate control system. Additionally, the control system of the battery bank depends on the SOC estimation accuracy substantially. Consequently, there are three significant hypotheses of this research:

- i. Designing a proper Battery Management System (BMS) based on State of Charge (SOC) estimation of the battery storage system.
- ii. Developing an effective control technique with the help of Artificial Neural Network (ANN) algorithm to optimize the battery performance.
- iii. Validating and implementing an experimental prototype of the BMS to integrate the PV-Battery integrated system successfully.

1.6 Research Questions

The traditional battery storage system contains less efficient to the advanced system accuracy. There must be a proper technique that can fix the over-charging/deep-discharging

either they alter rapidly, temporary or permanent. It should provide some enhanced protection as well by using BMS to take control the SOC estimation and enhance the entire system capability. There are further questions which were studied in this work, as are listed below:

- i. What is the current methodologies available in the literature to estimate SOC for BMS?
- ii. How to design an effective control scheme for maximizing the battery's performance?
- iii. How to validate the physical prototype of the BMS to prove the qualification of simulated model?

1.7 Research Gap

The prime research gaps which are mentioned in this study, can be listed as below:

- i. The proper simulation of BMS is an important task headed for regulating the SOC in it's safest zone.
- ii. The development of control strategy is significant caused by improving the battery performance through ANN technique.
- iii. The experimental validation is substantial aimed at confirming the appropriateness of the intended model.

1.8 Research Objective

The objectives of this research have been expected according to the problematic proclamations of the recent concerns such as SOC estimation of the battery cells and cell balancing of the battery strings. The objectives of this research are:

- i. To model and simulate a Battery Management System (BMS) based on State of Charge (SOC) estimation using MATLAB/Simulink software.
- ii. To develop a BMS control strategy using Artificial Neural Network (ANN) technique for maximizing the battery's performance.
- iii. To validate the proposed approaches with an experimental prototype.

1.9 Research Contribution

The major contributions of this research are the followings:

- i. A successful Battery Management System (BMS) can be performed based on State of Charge (SOC) estimation using MATLAB/Simulink software.
- ii. A proper control technique through Artificial Neural Network (ANN) can be designed to improve the battery performance comparing to the conventional method.
- iii. An experimental prototype can be arranged to approach the authentication of the simulated model.

1.10 Significance of Research

Since, energy conservation from solar cells can be used as an alternative to the depleting and expensive source of energy currently in Malaysia, the findings of this study will undoubtedly benefit the society. It is envisaged that the proposed research will establish a guideline for choosing appropriate penetration for SOC estimation scheme. The guide will prevent the battery from over-charging/deep-discharging of cell strings and improve the performance of the battery. It will discern the advantages of BMS to upstairs the control

system of PV RES. The experimental prototype will be supported to authenticate the simulated mode before industrialization. This study will make a significant impact in promoting PV-Battery integrated system to consumers.

1.11 Scope of Research

The scopes of this research are identified for the sake of focusing the expected upshots considerably:

- i. Battery Management System (BMS) based on State of Charge (SOC) estimation is simulated via MATLAB / Simulink software.
- ii. A control strategy using Artificial Neural Network (ANN) technique is developed towards maximizing the battery's performance.
- iii. An experimental prototype of the proposed PV-Battery integrated system is validated over and done with the dSPACE 1104 component.

1.12 Structure of Thesis

This thesis is categorized into five main chapters as depicted in Figure 1.3 which consists of Introduction, Literature Review, Research Methodology, Results and Discussion as well as finally Conclusion and Recommendation. The structure of thesis is described as below:

- i. Chapter 1 addresses the introduction of this study, including the research gaps and defining several basic techniques and technology.

- ii. Chapter 2 represents the literature review of research works from various sources relevant to this study.
- iii. Chapter 3 describes the Research Methodology for simulation modeling and laboratory experimentation to investigate, analyze and characterize the tasks of this research work.
- iv. Chapter 4 discusses the simulation and experimentation results as well as validation of the projected outcome.
- v. Chapter 5 focuses on the whole thesis compilation by following the research objectives as well as further recommendations for carrying out this work in future based on the problems faced.

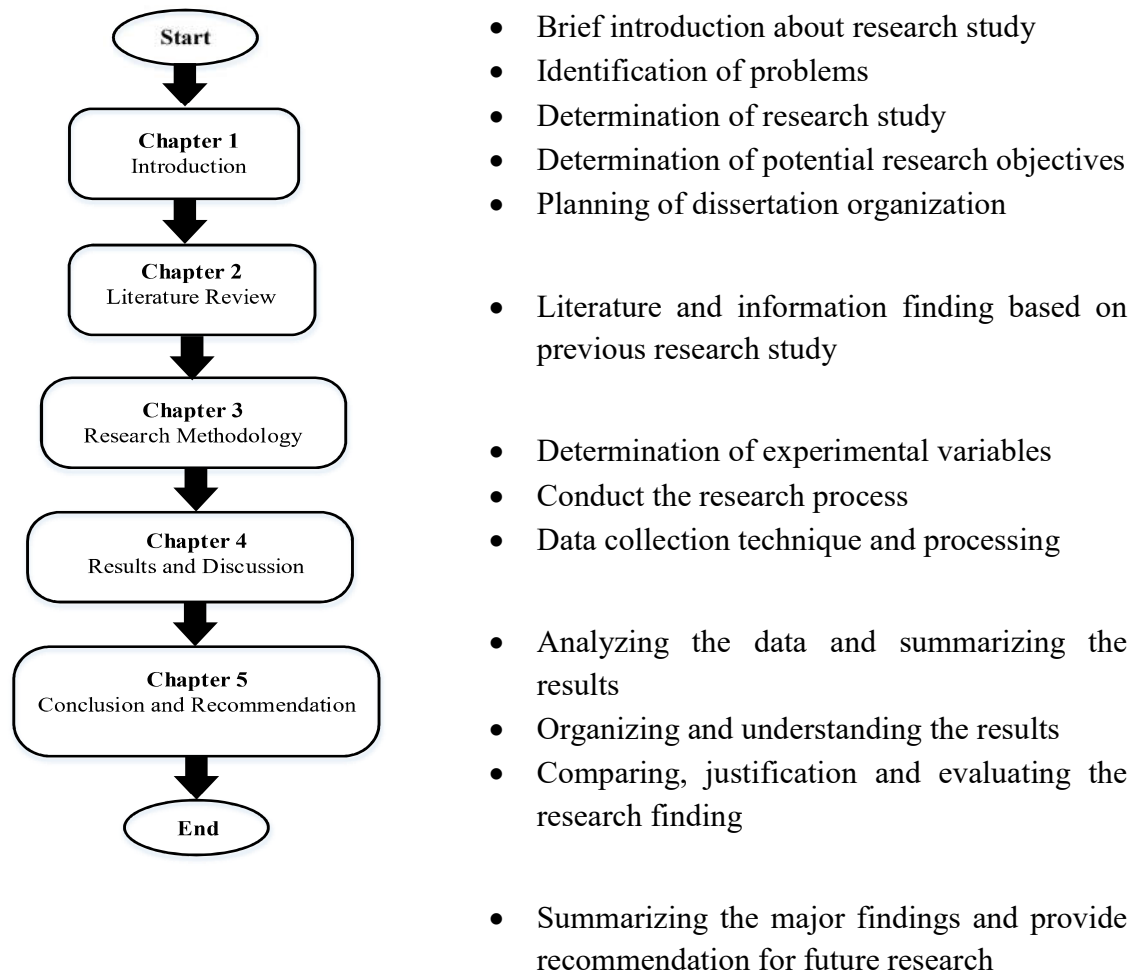


Figure 1.3: Dissertation Organization

CHAPTER 2

LITERATURE REVIEW

2.1 Chapter Overview

The entire potentiality of RESs is directly dependent on battery charge controlling scheme. In case of BMS, SOC estimation has become a soul interest for researchers due to its increasing applications of different aspects. For this reason, this chapter describes the related literature review of the previous novel works. Section 2.2 describes the SOC estimation techniques from different aspects including ANN algorithms. The related survey of novel BMS is surveyed in Section 2.3. Since this research work is related to PV-Load demand, the next literatures will be reviewed in Section 2.4. After a brief survey, the research gaps identified by this study are given in Section 2.5. At-last the summary of the chapter is given in Section 2.6.

2.2 Battery Management System (BMS)

The main goals of the power management strategy are to minimize the cost of the electricity that is imported from the grid and to maximize battery life by means of an adequate charging procedure, which sets the charging rate as a function of the MG state Salas-Puente et al. (2018) designed a Battery Energy Storage System (BESS) for the DC Microgrid where the power management is monitored through a Microgrid Central Controller (MGCC). The photovoltaic generation profile, load demand, and real-time prices of the electricity is informed to the MGCC with the help of a proper Microgrid operator. It estimates SOC of the battery bank and establishes a relationship between BESS and the main grid.

Barreras et al. (2016) improved a hardware-in-the-loop (HIL) simulator for BMS purposes in case of 32 numbers 40 Ah Lithium Ion Battery (LIB). A proper combination of hardware and software is necessary for extensive testing of BMS controllers. The system-level model was integrated with a multicell electrothermal LIB and applied on real time simulation by converting the model into C code. The BMS confirmation tests piloted cost and time efficiency (average system voltage 120 V) comparing to conventional methods. Lastly functional, nonfunctional and fault insertion tests were predicted for future extension of the research.

Mishra et al. (2019) described on Local Energy Management (LEM) technique for Wind/ Battery Energy Storage (BES) system in case of LIB. To compensate the production volatility of Wind Power Generation System (WPGS), Multi Kernel Ridge Pseudo Inverse Neural Network (MK-RPINN) algorithm was proposed as a result of obtaining an effective reduction of prediction error. A Doubly-Fed Induction Generator (DFIG) was considered as primary Distributed Generator (DG) with a Model Reference secondary controller to address the temperature impact of battery. The projected model was validated through TMS320 C6713 and MATLAB platform by comparing the resultant heating profile, SOC (%) and RMSE of the proposed MK-RPINN model with PINN and K-RPINN model. However, the proposed control system showed the DC link current (I_{batt}) uncertainty in the experimental initialization.

The reliability of electric vehicle is established by battery component which is composed of LIB BMS. Xu et al. (2018) proposed a distributed BMS to meet the consistency of design requests in that concern. The BMS was divided into two main parts namely control module and sampling module. The BMS was tested by following the electric load test (GB/T28046-4 standard). TPS5430 was selected as the conversion chip and RS232

communication channel was engaged between PCs through CAN bus. The BMS was tested in different temperatures, the external radiation emission and conduction emission satisfied the index requirements except for a few frequency locations.

Table 2.1: Summary of the research papers for BMS

Ref.	Technique	Functional	Result	Limitations
(Bonkile & Ramadesigan, 2019)	DAE	MATLAB, Intel® Core™ i7-6700 CPU	Prevent overcharging	Uncertainty of training data
(Barreras et al., 2016)	HIL Simulation	40-Ah Battery, C Code, HIL	Average system voltage 120V	Battery lifetime increment
(Mishra et al., 2019)	MK-RPINN	DG, TMS320 and MATLAB	RSE for Oct: 10 min (0.0118) and 30 min (0.0568)	Uncertainty of supply current
(Xu et al., 2018)	Kalman filter	TPS5430, RS232	BMS fulfilled the index requirements	BMS becomes uncertain for the variation of frequency parameter
(Ren et al., 2019)	EKF	DC/DC converter handovers energy among cells	Maximum cell variance was reduced to 3%	Long rest period as 2480-4250 sec

The series or parallel cell sequences decrease the capability of entire battery pack due to any weakened cell of the strings. The weak cell cannot perform charging and discharging scheme at the same moment with other cells of the string. To improve the efficiency of the storage system, Ren et al. (2019) proposed an improved BMS for LIB pack

to regulate the temperature, SOC and State of Health (SOH) EKF and active cell balancing technique was implemented to improve the accuracy of the SOC estimation and charge equalization respectively where the SOC variation was obtained only 3%. In the long run, the fragile cell was recommended to avoid from the string if the cell eminence can't be improved finally. More than a few number of research papers that subsidized for the BMS are summarized in Table 2.1.

2.3 State of Charge (SOC) Estimation

Among the battery monitoring functions, SOC is one of the most significant factors that should be controlled to prevent from the battery over-charging/over-discharging effects (Xiong et al., 2017). Although, the definition of the SOC varies from several researchers, commonly the SOC is demarcated from Equation 2.1 as the ratio of the current capacity $C(t)$ to the nominal capacity C_n .

$$SOC(t) = \frac{C(t)}{C_n} \quad \text{Equation 2.1}$$

Since the SOC estimated classification differs in various writings, a number of collected works sort out into four main categories which are given below:

- i. Direct Measurement
- ii. Adaptive Method
- iii. Filter based Estimation
- iv. Model-based Estimation

2.3.1 Direct Measurement

In this method, different kinds of physical parameters such as voltage, current, temperature, impedance etc. are used to estimate SOC by using a relationship or equations

of the factors (Pei et al., 2013; Xing et al., 2014). A few number of research papers which are promoted for the direct measurement based SOC estimation methods, are summarized in Table 2.2. From the outlines, four types of methods can be considered for the direct measurement based SOC estimation method, which are termed below:

i. Open Circuit Voltage Method

Although the liaison concerning the OCV-SOC varies into the batteries such as the lead acid battery and Li-Ion battery, the common calculations follow the Equation 2.2 and Equation 2.3,

$$V_{OC}(t) = e_1 * SOC(t) + e_0 \quad \text{Equation 2.2}$$

$$SOC = f^{-1}(OCV) \quad \text{Equation 2.3}$$

Where, $SOC(t)$ is capability of SOC for the Battery at time t ; e_0 is terminal voltage of battery at $SOC = 0\%$; e_1 can be found from e_0 and $V_{OC}(t)$ at $SOC = 100\%$; R_p is Polarization resistance, C_p is Polarization capacitance, R_s is Series resistance, i is Current: Positive value is used when discharge and negative value is used when charge.

Even if the SOC is determined from a table with the continuous measurement of the cell voltage, the requirement of high tenacity of voltage sensor and appropriate time duration shows the main weakness of a system (Tong et al., 2015; Dang et al., 2016; Baccouche et al., 2017). Wang et al. (2017) investigated on SOC estimation by two tests namely the incremental OCV test and Low current OCV test. Two types of batteries Nickel Cobalt Manganese Oxide (NMC) and $LiFePO_4$ (LFP) were implemented by means of a combinational algorithm which are unscented KF (UKF) and H_∞ filter. A battery structure of the Thevenin model was demonstrated with the polarization parameters, which has been shown in Figure 2.1. Though the incremental test showed better performance comparing to

low current test, the battery relaxation time takes more than 2 hours delay. Dang et al. (2017) applied the Controlled Auto-Regressive and Moving Average (CARMA) model on the EV-BMS by the BPNN algorithm. Feedforward-Feedback (FFFB) compensation was utilized to increase the truthfulness of the SOC estimation, where the Mean Absolute Error (MAE) was acquired nearly 1.247%.

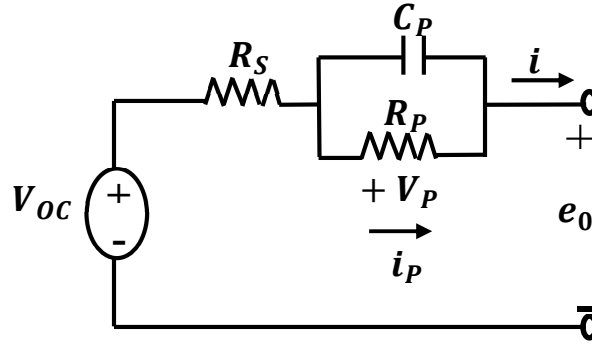


Figure 2.1: Thevenin battery model structure (Baccouche et al., 2017)

Devarakonda & Hu (2015) estimated SOC for lead-acid battery (LAB) through second order Thevenine model. Above 80% and below 40% SOC, the battery was required comparatively high rest time and so this range was recommended for the useful practice in case of LAB. Dong et al. (2016) tried to reduce the complication of the SOC estimation accuracy for EV or smart grid BMS. Invariant-Imbedding Method (IIM) algorithm was implemented to estimate OCV hysteresis of the battery model. However, nearly $\pm 2\%$ error was attained by the Dynamic Stress Test (DST) scheme as a consequence of the noise sensitivity instrumental faults.

ii. Terminal Voltage Method

A linear relationship can be found between the Electromotive Force (EMF) and the SOC of a battery. Since the terminal voltage of a battery depends on the voltage descent owing to the internal impedances at discharging moment, for this reason the terminal voltage

of a battery almost linear proportional to SOC as well (Coleman et al., 2007). In case of this method, the SOC can be calculated by following Equation 2.4 to Equation 2.5.

$$\frac{ds}{dt} = \eta \frac{i}{36Q_a} \quad \text{Equation 2.4}$$

$$Q_a = Q_{a0} - Q_f \quad \text{Equation 2.5}$$

Where, η is Faraday efficiency, Q_a is Actual capacity of the battery, Q_{a0} is Initial capacity of the battery, Q_f is Capacity fading due to the aging effect.

Ren et al. (2019) experimented on the LIB by the EKF algorithm where the DC/DC converter was used to allocate energy from one battery cell to others. In this experiment, the maximum cell variation for SOC was reduced to 3% (from Figure 2.2), however the rest period of EV was found long time i.e. 2480 – 4250 sec. Wang et al. (2012) carried out the trial by the SimPower System Toolbox in MATLAB software on a single cell of the Li-ion battery where the true and estimated error was found as 0.8 and 0.8121 respectively.

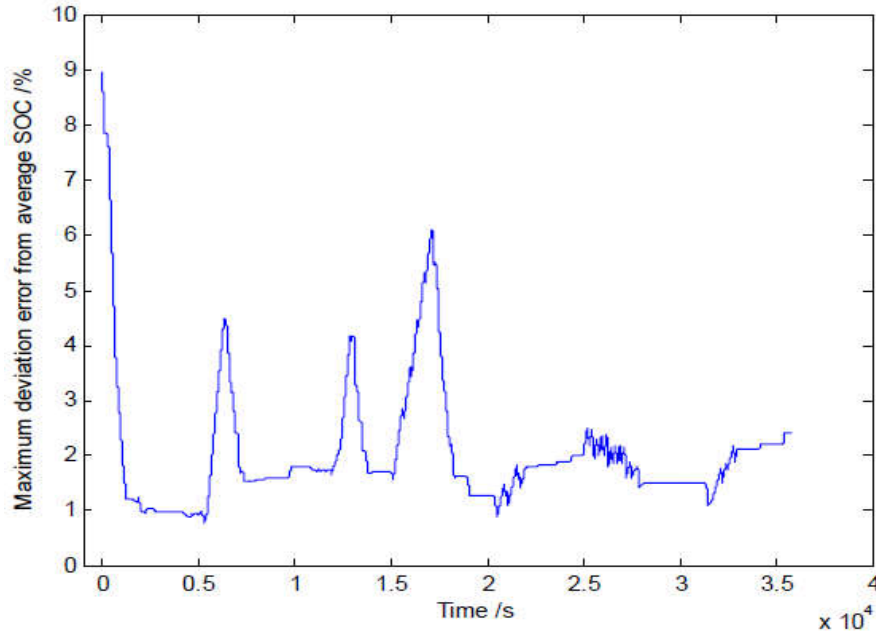


Figure 2.2: Time vs maximum Deviation Error from average SOC (Ren et al., 2019)

iii. Impedance Method

In this method, the battery impedances are restrained from the ac frequencies where the voltage and current are memorized properly at charging and discharging moment (Carkhuff et al., 2018; Dai et al., 2018). However, the dependency of battery impedance parameters on its lifecycle and the scarcity of the accuracy of the impedance sensitive factors show the prime weakness suggestively of this method (Waag et al., 2013). Generally, the resistance R_s and inductor L_s designate the battery behavior of the model at high frequency (shown in Figure 2.3). The frequency section is demonstrated by a Constant Phase Element (CPE) with a parallel resistance R_p . The impedance of the CPE can be stated as,

$$Z_{CPE}(s) = \frac{1}{Qs^\alpha} \quad \text{Equation 2.6}$$

$$Z_{model}(s) = L_s + R_s + \frac{R_p}{1 + R_p Q_p s^\alpha} \quad \text{Equation 2.7}$$

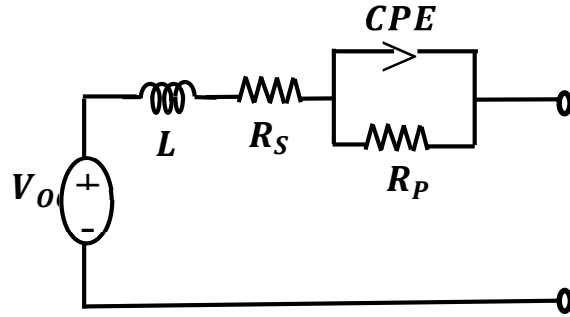


Figure 2.3: Battery impedance equivalent circuit model (Dai et al., 2018)

Zhu et al. (2018) fashioned a corresponding circuit model for the $\text{LiNi}_{0.80}\text{Co}_{0.15}\text{Al}_{0.05}\text{O}_2$ battery where the Odd Random Phase (ORP)-Electrochemical Impedance Spectroscopy (EIS) and the symmetric cell tactic were implemented appropriately. From 3.7 V to 4.2 V, SOC showed better performance which depends on the Charge Transfer Resistance (R_{ct}) of $\text{LiNi}_{0.80}\text{Co}_{0.15}\text{Al}_{0.05}\text{O}_2$ (NCA) mostly. On the other hand,

in the low electrode potential region (<3.7 V) and high electrode potential region (>4.2 V), R_{ct} becomes high because of the change of the crystal structural materials.

Skoog and David (2017) applied the impedance spectroscopy method for three several types of Lithium-ion pouch cells considering the SOC and temperature from 10% to 90% and -10 °C to +40 °C respectively. They used the RMSE of voltage in long dynamic load cycles to appraise the frequency-domain equivalent circuit model. In case of comparison, the R+2RC showed improved enactment (RMSE 15.46 mV) than the R+6RC (18.77 mV) model. Huang et al. (2016) employed a 15.4 Ah NCM/graphite LIB for SOC estimation where the Warburg impedance percentage was applied to evaluate the ability of the battery performance. The diffusion resistance $Z_{W\infty}$ and the charge transfer resistance R_2 rise affectedly as soon as the SOC reduces below 26.5%. Therefore, battery operation under 20% SOC forbidden from this experimentation.

iv. Coulomb Counting Method

Presently Coulomb Counting (CC) method is also recognized as the ampere-hour method according to it's instant designs. Mathematically using Equation 2.8, the SOC can be defined from the CC method,

$$SOC(t) = SOC(t_0) + \frac{1}{C_n} \int_{t_0}^{t_0+t} I_{bat}(d\tau) \quad \text{Equation 2.8}$$

Where, $SOC(t_0)$ is Preliminary SOC of the battery; C_n is Nominal capacity of the battery; I_{bat} is Charging/Discharging current of the battery.

Since several types of factors such as temperature, discharging current, battery cycle life, aging effect etc. often affect the accuracy of the Coulomb Counting method, a modified Coulomb Counting method has been anticipated to progress the conventional method.

Table 2.2: Summary of the research papers for Direct measurement based SOC estimation methods

Ref.	Algorithm	Functional	Result	Limitations
(Wang et al., 2017)	H ∞ -UKF	Incremental test & Low current test	Incremental test is better	Relaxation time delay
(Pan et al., 2017)	GMEKF	UDDS	RMSE of GMEKF < EKF	Uncertainty of charge status
(Campestrini et al., 2017)	EKF	OCV was measured in 4 several temp (0 to 40 °C)	Error 3.5%-6.5%	Error is high
(Dang et al., 2017)	BPNN-FFFB	EV-BMS	MAE 0.3325%-1.2478%	Modeling and fitness error
(Ren et al., 2019)	EKF	DC/DC converter handovers energy among cells	Maximum cell variance was reduced to 3%	Long rest period 2480-4250 sec
(Zhu et al., 2018)	ORP-EIS	Used an equivalent circuit model	SOC showed better performance in 3.7 to 4.2V	Resistance rises for the crystal material
(Skoog & David, 2017)	Frequency domain fitting	3 different types of cells	RMSE 15.46 mV for R+2RC model	Designed for low-frequency ECM
(Westerhoff et al., 2016)	EIS	Pouch cell>35Ah	Error maxima<5%	Temperature was assumed constant as 20 °C
(Xie et al., 2018)	Peukert's Law	Frequency controlled current sampling	Error maxima 2.69%	Error occurs at partially discharging time
(Fotouhi et al., 2018)	ANFIS-CC	UDDS test	Mean error 4% & error maxima 7%	Error is high

The corrected current $I_c(t)$ belongs to the quadratic relationship with the conventional current $I(t)$ which can be deliberated from the mathematical Equation 2.9. Furthermore, the accuracy of the modified CC method has been obtained more superior comparing to the conventional CC method on account of this corrected current $I_c(t)$ (Cheng et al., 2011; Chang, 2013; Lee et al., 2015).

$$I_c(t) = m_2 I(t)^2 + m_1 I(t) + m_0 \quad \text{Equation 2.9}$$

Where, m_2 , m_1 and m_0 are the constant values which can be obtained from the practiced investigational statistics.

Xie et al. (2018) studied on the CC SOC estimation by the combination of Peukert's Law and coulombic efficiency algorithm because of the discharging procedure and charging procedure respectively. The frequency-controlled current sampling resolution was improved to obtain an advantageous cooperation between sampling frequency and accrual exactitude. Even though the error occurs at partial discharging instants, the maximum error was obtained 2.69%. As the observation of Li-S cell model is delinquent due to the specific shape of the cell's OCV curve, Fotouhi et al. (2018) implemented the combination of Adaptive Neuro-Fuzzy Inference System (ANFIS) and CC method experimentally as shown in Figure 2.4 where the mean error and error maxima was acquired 4% and 7% respectively. The Urban Dynamometer Driving Schedule (UDDS) test was utilized to verify the proposed model accuracy, but the necessity of the huge amount of training data for the ANFIS algorithm as well as the temperature and aging effect affects the potentiality of the projected model. Ng et al. (2009) considered LIB from CGR 18650D Panasonic Co. for the OCV-CC SOC estimation where only 1% error was estimated. However, temperature increases drastically when the discharging rate occurs more than 0.8 C.

2.3.2 Adaptive based estimation

The adaptive systems are self-processing method that can be spontaneously reformed to fulfill it's targeted value (Chaoui & Ibe-Ekeocha, 2017; Lipu et al., 2018). In recent times, BPNN, Radial Basis Neural Network (RBNN), Fuzzy Neural Network (FNN) and SVM SOC estimation methods have been established straightforwardly caused by the artificial intelligence improvement. The adaptive methods offer good explanation in case of batteries chemical effect and nonlinear charge appearances (Kang et al., 2014).

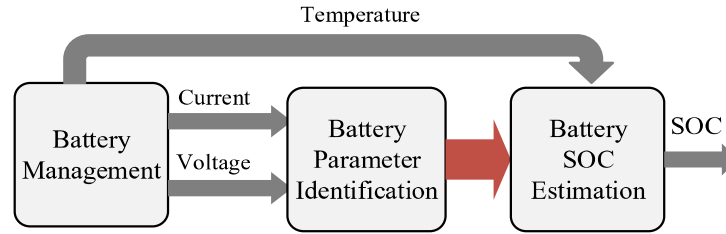


Figure 2.4: Procedure of SOC estimation technique (Fotouhi et al., 2018)

Table 2.3 represents the summary of the research papers that contributed for the adaptive system based SOC estimation method.

i. BackPropagation Neural Network Method

The BackPropagation Neural Network (BPNN) is widely held to estimate SOC because of its self-learning and nonlinear characteristics (Shahriari & Farrokhi, 2013; Dong & Wang, 2014; Hussein, 2015). As the affiliation between the input and the SOC estimation is non-linear, the SOC estimation based on artificial neural network forecasts the up-to-date SOC by means of latest account of voltage, current and the battery temperature. The BPNN constitutes of an input layer, an output layer and a hidden layer (Husnayain et al., 2014; Wang et al., 2016). In case of SOC estimation procedure, the layers contain three input

neurons (voltage, current and temperature), one output neuron (SOC) and n number of hidden neurons which has been shown in Figure 2.5.

Hannan et al. (2018) studied on the Backtracking Search Algorithm (BSA) algorithm based BPNN SOC estimation for the LIB. The DST and Federal Urban Driving Schedule (FUDS) drive profiles were smeared at three different temperatures (0, 25 and 45 °C) and ensued the reduction of RMSE at 25 °C for DST was 34%, 62%, 56% as well as for FUDS was 59%, 58%, 61% respectively comparing to Radial Basis Function Neural Network (RBFNN)-BSA, Generalized Regression Neural Network (GRNN)-BSA and Extreme Learning Machine (ELM)-BSA models.

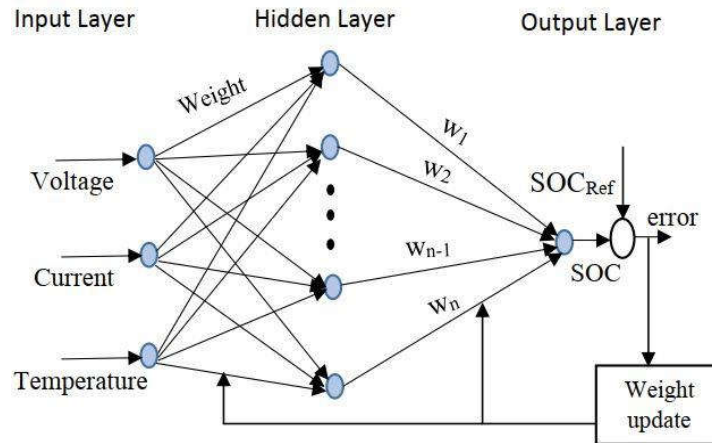


Figure 2.5: Structural design of BPNN based SOC estimation scheme (Chang, 2013)

Leveringhaus and Hofmann (2011) considered the combination of PCO and Particle Swarm Optimization (PSO) algorithm for the SOC estimation on the LIB. The achieved RMSE of several tests such as Beijing Dynamic Stress Test (BJDST) 0.58%, FUDS (0.72%) and US06 (0.47%) showed better results comparing to RBFNN. Husnayain et al. (2014) tried to use the Lead-acid battery for devising the optimum employment with the BPNN algorithm. The projected result was compared with two other methods namely OCV and CC method where LabVIEW and MATLAB softwares were utilized to investigate the

experiment with NI DAQ USB 6008 component. The maximum average error was obtained less than or equal to 0.893%, however the temperature and aging effects should be trialed for the real life application.

ii. FNN method

The adaptive neuro-fuzzy inference system (ANFIS) and the local linear model tree is the foremost two types of classification for Fuzzy logic Neural Network based SOC estimation method (Wu et al., 2012; Awadallah & Venkatesh, 2016). ANFIS constitutes of the Fuzzy and Neural Network compensations that is notable to model and recognize the patterns of the system (Fleischer et al., 2013; Dai et al., 2015). Zahid et al. (2018) applied Neuro-Fuzzy algorithm with the MANHATTAN driving cycle where the Maximum absolute error for the SOC estimation was less than 0.1% comparing to the Backpropagation and Elman neural network. Though the training and testing points were gathered by the ADVISOR software, the unsure of the Subtractive Clustering (SC)-ANFIS training and testing step showed some uncertainty of the proposed model.

Zhang et al. (2015) tested on PLF08150240 LIB by the fuzzy logic control-neural network procedure. Genetic Algorithm was applied on the two stage DC/DC converter where the ampere-hour counting scheme with the equivalent circuit model to obtain dynamic battery SOC from the static SOC via the neural network. Though the Energy efficiency was found 93.1% comparing with the mean-difference technique through the UDDS test for HEV, the cost of the experiment was not involved in this study. Fleischer et al. (2013) applied TFVP for the power prediction scheme of the Li-Ion cell and approached the ANFIS system to estimate SOC by the REKF algorithm. Though the absolute error was obtained less than 1%, the instrumental measuring inaccuracy was the delinquent of the proposed

method. Xu et al. (2012) projected the Kalman filtering SOC estimation with the help of Stochastic Fuzzy Neural Network (SFNN) which can affect the noisy participation to design the battery nonlinear dynamic. He applied the FUDS to verify the SOC approximation (maximum error 0.6%) upon the 80 Ah Ni/MH battery. The exhaustive arrangement of the SFNN node is shown in Figure 2.6. Here, x_j^l are the inputs of the SFNN model, y_j^l is the output, τ_j^l is the activation function. Moreover, k and l signify the layer number and describing function of the nodes respectively.

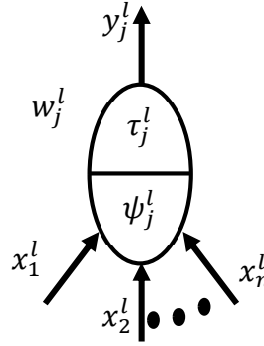


Figure 2.6: Nodal structure of SFNN (Xu et al., 2012)

iii. RBFNN method

In case of the inadequate statistics of a system, the Radial Basis Function Neural Network (shown in Figure 2.7) is a useful methodology to estimate SOC (Han & Qiao, 2012; Zhang et al., 2013; Mahapatra & Negi, 2016). In a certain set, the RBFNN can be applied to explore the liaison between the reference order and the comparative data. In case of Radial Basis Function based SOC estimation technique as mentioned in Equation 2.10 to Equation 2.11, output $Y(X)$ is the combination of the hidden layer neurons with the synaptic weights w_i .

$$Y(X) = \sum_{i=1}^N w_i \varphi_i(X, C_i) \quad \text{Equation 2.10}$$

$$\varphi_i(X, C_i) = \varphi(||X - C_i||) \quad \text{Equation 2.11}$$

Here, N is the number of hidden layer neurons and $\varphi_i(X, C_i)$ is a radial basis function that is the difference between the input vector $X = (x_1, x_2, \dots, x_n)$ and the center $C(C_i \in R^n)$.

Chen et al. (2016) signified the robust sliding mode observer (RSMO) and applied the Forgetting Factor Recursive Least Square (FFRLS) algorithm of a Battery Equivalent Circuit Model (BECM) for the SOC valuation. The RMS of UDDS showed enhanced presentation (2.3214%) comparing to Highway Fuel Economy Test (HWFET) 2.3318%, but the thermal regularity of the LiPB was suggested for the research advancement.

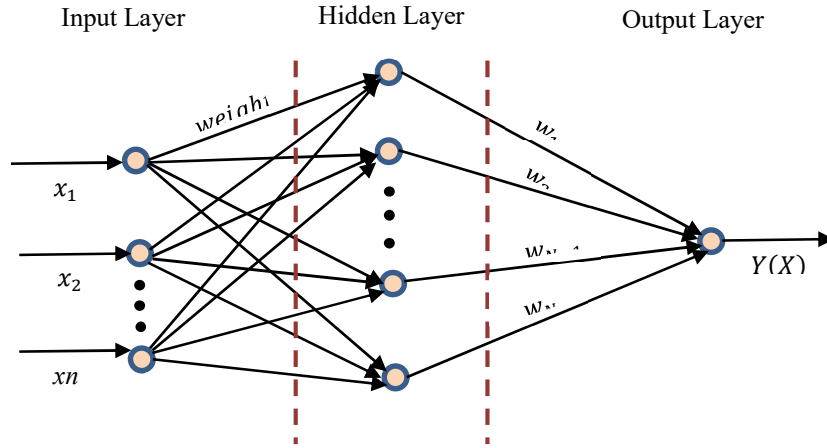


Figure 2.7: Structural design of RBNN based SOC estimation scheme (Chang, 2013)

Sun et al. (2016) studied on the twelve series-connected LiPB battery cells. RBFNN based uncertainty quantification algorithm was anticipated to construct Response Surface Approximate Model (RSAM). Though the MAE for SOC estimation was obtained as less than 2%, the cost analysis of the projected method has to be realized again. Chang (2013) conducted a test for the RBFNN SOC estimation with combination of Orthogonal Least-Squares (OLS) and Adaptive Genetic Algorithm (AGA) algorithm. The PFX2021 battery tester was utilized for the SOC estimation of the LFB discharging conditions where the

RBFNN obtained more accurate result Average Absolute Percentage Error (AAPE) 0.021%, Maximum Absolute Percentage Error (MAPE) 1.82% than the BPNN and Coulomb integration method.

iv. SVM method

In case of classification of pattern recognition and regression difficulties, the Support Vector Machine (SVM) has been practiced suitably. The SVM technique has been applied in nonlinear estimation frequently comparing to the least-square estimation owing to the insensitiveness of the minor variations (Wei et al., 2013; Surendar et al., 2015; Zhang & Wang, 2018). From Equation 2.12 to Equation 2.13, x is the input vector containing battery parameters, μ is coefficient, σ is deviation and $\phi(x)$ is the diagramming from original to the targeted space, the target function and the regression R of the SVM can be obtained from the following equations,

$$f(x) = \mu\phi(x) + \sigma, \mu \in R^n \quad \sigma \in R \quad \text{Equation 2.12}$$

$$R[\vec{w}, b, \beta] = \frac{1}{2} ||\vec{w}||^2 + C \sum_{j=1}^L (\beta_j^+, \beta_j^-) \quad \text{Equation 2.13}$$

In Equation 2.13, $\frac{1}{2} ||\vec{w}||^2$ is the flatness function and the regulation constant C is used to trade-off between the margin and the magnitude of the slack variables β_j^+ and β_j^- .

Sheng et al. (2015) trained the Fuzzy- Least Square Support Vector Machine for Regression (LSSVR) algorithm on the COMS-EV LiFePO₄ battery and compared the result with the Neural network and PSO- Support Vector Machine for Regression (SVR). With the exception of the RMSE of the proposed method, the maximum error (0.3%) and the average error (0.28%) offered recovering result assimilating to other two methods.

Table 2.3: Summary of the research papers for Adaptive based SOC estimation methods

Ref.	Algorithm	Functional	Result	Limitations
(Hannan et al., 2018)	BSA	DST and FUDS EV	BPNN-BSA model is better	Experimental is necessary
(Leveringhaus & Hofmann, 2011)	PCO+PSO	BJDST, FUDS, US06 cycle	RMS 0.47%	Experimental is necessary
(Husnayain et al., 2014)	BPNN	LabView-MATLAB	Error<0.893 %	Low battery lifetime
(Zahid et al., 2018)	SC-ANFIS	MANHATTAN	MAE≤0.1%	Uncertainty of training and testing data
(Zhang et al., 2015)	GA	UDDS tests for HEV	Efficiency 93.1%	Low efficiency
(Dai et al., 2015)	ANFIS	Ambient chamber VOTSCH C4-180 Pro	Charging & discharging	Increment of battery lifetime
(Chen et al., 2016)	FFRLS	RSMO	RMS is 2.3214%	Thermal irregularity
(Sun et al., 2016)	RBFNN	Series-connected 12 cells	MAE<2%	Experimental is necessary
(Kumar et al., 2018)	RBFNN	Electric bus	Error maxima 0.025%	Research on different battery
(Bi et al., 2012)	Fuzzy-LSSVR	COMS-EV	e _{MAX} 0.3%, e _{AVE} 0.28%	MSE is larger than others
(Hu et al., 2014)	Double search technique	ADVISOR	SVR is enhanced	Experimental is necessary
(Anton et al., 2013)	Cross validation	DST	Accuracy improves more than 6%	Uncertainty of charge status

Table 2.3 continued

(Álvarez Antón et al., 2013)	Cross validation	UOB Lab	Coefficient of determination is 0.97	Research on Lead acid battery
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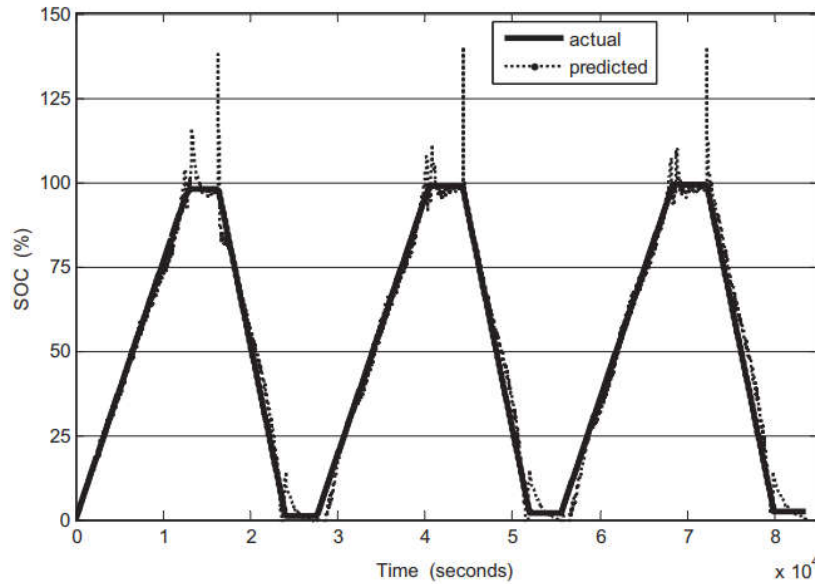


Figure 2.8: Comparison between actual and predicted SOC estimation (Antón et al., 2013)

Hu et al. (2014) utilized the ADVISOR software for the SVR SOC estimation by the double search procedure. Eight types of cyclic situations and seven kinds of battery parameters were implemented to estimate the accuracy of the proposed method. Alvarez et al. (2013) experimented the SVM SOC estimation on the LiFeMnPO_4 with the cross validation technique. The projected scheme upgraded 6% more exactitude by the DST cycle with the insufficiency of cost engrossment. Antón et al. (2013) tested on the LiFePO_4 by the Cross validation algorithm. The resultant coefficient was determined 0.97 by the Oviedo Battery Laboratory (UOB) Lab. The resultant actual SOC and predicted SOC value was nearly same with respect to time as shown in Figure 2.8. But the study on another cells was suggested for future research.

2.3.3 Filter based estimation

In case of filter based estimation, the feedback technique is applied to modify the output by following its input. It is a self-designing system that can regulate the output routinely (Arablouei et al., 2014; Din et al., 2016; Meng et al., 2016). Table 2.4 represents the summary of the research papers that contributed for the filter based SOC estimation method. Amongst quite a few types of methodologies, three types of methods can be brought into being from the literatures to estimate SOC steadfastly, which are described below:

i. Kalman Filter method

The battery SOC estimation established by the real-time quantity is problematic and costly to measure precisely (Li et al., 2016; Lim et al., 2016). From Yang et al. (2017), Thevenin model was preferred to model the battery configuration (shown in Figure 2.9).

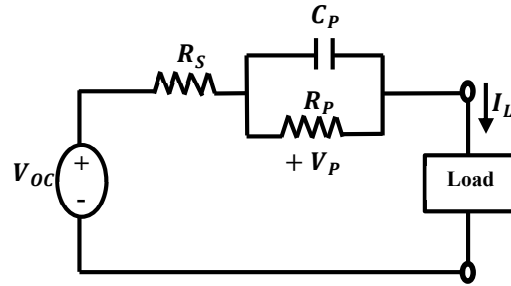


Figure 2.9: Thevenin model to describe KF method (Yang et al., 2017)

If V_{OC} is the Open Circuit Voltage, R_S is the ohmic resistance, R_{pr} is the polarization resistance, C_{pc} is the equivalent capacitance, V_t is the terminal voltage, V_p is the polarization voltage and I_L is the load current, the contribution of the model can be conferred from Equation 2.14 to Equation 2.15.

$$V_p = -\frac{V_p}{C_{pc}R_{pr}} + \frac{I_L}{C_{pc}} \quad \text{Equation 2.14}$$

$$V_t = V_{OC} - V_p - I_L R_s$$

Equation 2.15

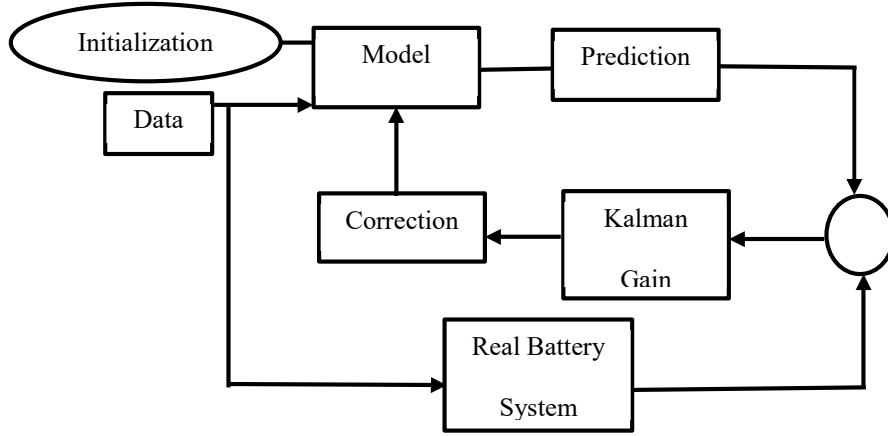


Figure 2.10: Iteration diagram for Kalman filter method (Rivera-Barrera et al., 2017)

$$x_{p+1} = A_p x_p + B_p u_p + G_p \quad \text{Equation 2.16}$$

$$y_p = g(x_p, u_p) + \delta_p \quad \text{Equation 2.17}$$

$$A_p = \begin{bmatrix} \exp(-\Delta t/\gamma) & 0 \\ 0 & 1 \end{bmatrix} \quad \text{Equation 2.18}$$

$$B_p = \begin{pmatrix} [1 - \exp(-\Delta t/\gamma)] R_{pr} \\ -\Delta t/C \end{pmatrix} \quad \text{Equation 2.19}$$

$$C_p = \begin{bmatrix} -1 & \frac{dV_{OC,p}}{dS_p} \end{bmatrix} \quad \text{Equation 2.20}$$

$$g(x_p, u_p) = V_{OC,p} - I_{L,p} R_s - V_{p,p} \quad \text{Equation 2.21}$$

Moreover as mentioned in (Rivera-Barrera et al., 2017) in case of state space model of Equation 2.16 to Equation 2.21, let x_p is the State vector, y_p is the output vector, u_p is the Input vector, A_p is the Plant matrix, B_p is the Input matrix, C_p is the output matrix, S_p is the SOC of p th sample time. Here $\gamma = C_p R_{pr}$ is the time constant, G_p is the Gaussian white noise with zero mean and the covariance P_p , δ_p is the Gaussian white noise with zero mean and the covariance S_p . In Equation 2.21, $g(x_p, u_p)$ is known as the nonlinear output function. In this regard, the detailed iteration diagram of the KF algorithm is shown in Figure 2.10.

Wang et al. (2018) experimented on the Series HEV LiFePO_4 by the UKF and an upgraded procedure to diminish the sampling noise with the enhancement of SOC perfection. Though the research was accomplished over a single battery with the recommendation of further research on the cells discrepancy, the estimation error and the reduction of fuel depletion was obtained 1.5% and 5% respectively. Zheng et al. (2018) tried out the Differential Voltage (DV) exploration on the LIB for the combination of EKF and PF SOC estimation. The resultant Maximum Absolute Error (MmAE) and RMSE was established 1.75% and less than 1.10% respectively, in addition to the relationship of temperature and the model was predicted for the prospective research. Huang et al. (2018) applied the combination of UKF and EKF algorithm on the LiNMC battery with the first order RC equivalent circuit model and the combined model to estimate the enactment of the algorithm. Multi-Swarm Particle Swarm Optimization (MPSO) showed superior performance comparing to Recursive Least Square (RLS), nevertheless SOC falls its accuracy for the incremental temperature.

Ramadan et al. (2017) studied a comparison between Watrin (2013) and Bo et al. (2015). A Second order equivalent circuit was modeled with the execution of EKF algorithm. Bo et al. (2015) performance was better comparing to Watrin (2013), conversely to obtain more accuracy on SOC estimation error, the Series, parallel and hybrid battery connections were suggested for the impending research. Peng et al. (2017) projected the AUKF with a noise statistics estimator to establish the SOC of BESS precisely. The application of noise statistics of large-scale BESSs and the estimation of SOC by EKF or UKF is typically erroneous. The noise statistical estimator was modeled and the SOC was established by the standard UKF. The simulation and experimental results (RMSE 0.0163, MAE 0.0149) were compared with the EKF and UKF algorithm. The assessment of the proposed method was

enhanced comparing to other two methods. Nevertheless, the cell inconsistency due to the discrepancy of the battery model parameters was focused as a supreme limitation for this proposed model.

ii. H infinitive method

To limit the influence of erroneous disturbance on the SOC estimation outcome, H infinitive (H_∞) is a dominant apparatus (Lin et al., 2016; Muhammad et al., 2017). The measurement inaccuracy and system noise can be restricted under a fixed attenuation level by the H infinitive method. From (Liu et al., 2018), a general model of (H_∞) is shown in Figure 2.11 by which the State of Charge estimation accuracy can be improved precisely. To implement H_∞ filter based State of Charge estimation method, Equation 2.22 to Equation 2.26 was considered as shown below,

$$\begin{pmatrix} z \\ v \end{pmatrix} = P(s) \begin{pmatrix} w \\ u \end{pmatrix} \quad \text{Equation 2.22}$$

$$P(s) = \begin{bmatrix} P_{11}(s) & P_{12}(s) \\ P_{21}(s) & P_{22}(s) \end{bmatrix} \quad \text{Equation 2.23}$$

Here, P is a plant matrix where u and w are the exogenous and manipulated inputs respectively. Two outputs are obtained from the plant matrix, first is the error signal z which has to be minimized and the other one is v that is used to govern the system. The purpose of this method is to find the gain value K of the controller for which $F_t(P, K)$ is reduced. Zhao et al. (2018) implemented the HEKF on the 3200 Lithium-ion cells by the New European Driving Cycle (NEDC) to reimburse the error not more than 2%. The H infinitive Extended Kalman Filter (EKF) as shown in Figure 2.12 was applied on the two models (HEKF-RC and HEKF-2RC) which showed better performance comparing to the conventional EKF model.

$$u = K(s).v \quad \text{Equation 2.24}$$

$$z = F_t(P, K).w \quad \text{Equation 2.25}$$

$$F_t = P_{11} + P_{12} K(I + P_{22} K)^{-1} P_{21} \quad \text{Equation 2.26}$$

Though the dearth of battery aging was recommended for the future investigation in this paper, the BMS of EV was established with the SOC assessment. Liu et al. (2018) exasperated the one order ECM of the LIB with the help of Variable Forgetting Factor Recursive Extended Least Squares (VFFRELS) that is a combination of Incremental Autoregressive and Moving Average (IARMA). Adaptive H-Infinity Filter (AHIF)- Δ OCV technique was applied to investigate the simulated model and compared with the Adaptive Extended Kalman Filter (AEKF) and AEKF- Δ OCV method. From this research, only 0.11% and 0.18% Average Absolute Error (AAE) was attained for the DST cycle and FUDS cycle respectively as well as the temperature effect was commended for the future research.

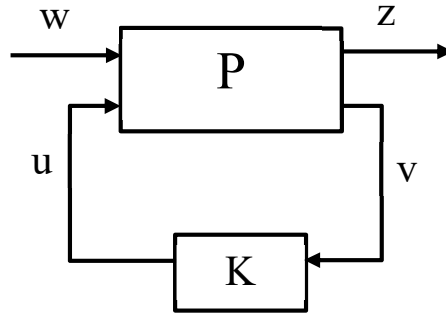


Figure 2.11: General structure of the H_∞ method (Liu et al., 2018)

Xiong et al. (2017) trialled on the fully charged/discharged battery by implementing the H infinity filter with the OCV-SOC estimation method to lessen the time and cost roles of the LiFePO₄ battery. Two tests namely capacity test and Hybrid Pulse Power Characterization (HPPC) test were applied to authenticate the prospective method where the SOC error can be reduced less than 1%. Moreover, the investigation of not fully charged/discharged battery was mentioned for imminent research. Yu et al. (2017) proposed

a combined algorithm named as H-Infinity Filter (HIF)-UKF method and compared this method with the PSO-UKF based SOC estimation by the DST test and UDDS test. 10, 25 and 40 °C temperatures were used to attest the suggested method and the SOC estimation error becomes low comparing to another method in every cases. Though this method joins to the targeted SOC estimation fastly, the inaccuracy was notified at large disparity of temperature.

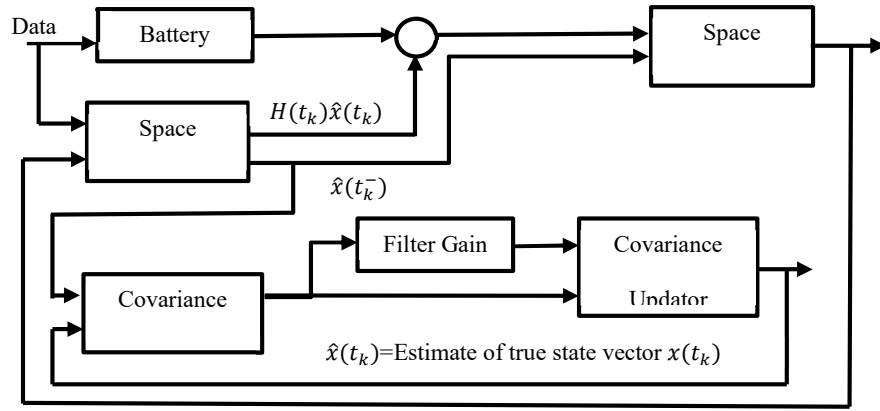


Figure 2.12: HEKF Block diagram for SOC estimation (Zhao et al., 2018)

iii. Recursive method

Recursive Least Square is based on the adaptive filter scheme where the coefficients are found recursively as well as the least square cost function is minimized according to its input signals. Though the RLS algorithm is a speedy pattern comparing to others, the errors can be obtained due to the computational complexity (Kim et al., 2015; Guo et al., 2016; Wei et al., 2016). For simplicity to describe from (T. Kim et al., 2015), Figure 2.13 can be considered where C is the cost function that has to be minimized by the forgetting factor μ . If $d(n)$ is the looked-for signal and $e(n)$ is the error signal with the filter coefficients ω_n , the cost function can be calculated from the following Equation 2.27 to Equation 2.28.

$$C(\omega_n) = \sum_{j=1}^n \mu^{n-1} e^2(j); 0 < \mu < 1 \quad \text{Equation 2.27}$$

$$e(n) = \partial(n) - \hat{\partial}(n) \quad \text{Equation 2.28}$$

Zhang et al. (2018) studied on the resistor and capacitor of the Battery ECM by the Decoupled Weighted Recursive Least Squares (DWRLS) method and showed a comparison with the Least Squares (LS) method. Since the slow and fast dynamics characteristics are perceived in the battery section, approximately 1% accuracy was obtained in the proposed system. It was observed that 5 mV OCV differs when the subject of temperature decreased from 25 °C to 0 °C with the aging effect.

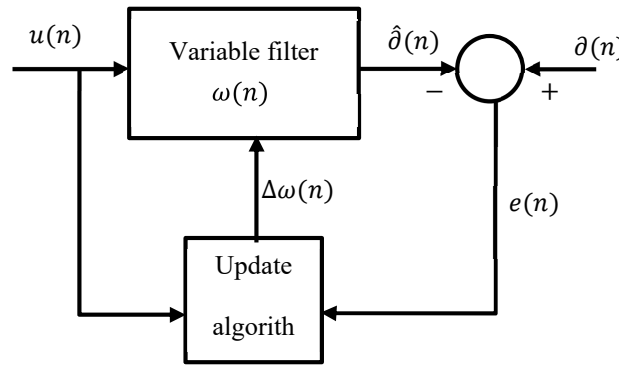


Figure 2.13: Fundamental structure of the RLS method (T. Kim et al., 2015)

Wei et al. (2017) experimented on the 2200 mAh LIB where the Multiplies, Divides and Square Roots (MADs) were utilized to estimate the model accuracy. Recursive Total Least Squares (RTLS)-Based two experiments for High and Low level current excitation were compared with the RLS-EKF, RLS-AEKF and RLS-HIF methods in where the MAE (0.828% & 0.882%) were the least in every time for the proposed method. Since the coefficients of the techniques, which were utilized to elucidate the Rayleigh quotient (RQ), based RTLS, the temperature effect was predicted for the binary function of the SOC estimation procedure. Duong et al. (2015) obtained less than 2.8% absolute error by applying the MAFFRLS algorithm on the LiFePO₄ for the EV. The project was tested with the UDDS

and NEDC driving cycles as well as compared with the unadventurous Single Fixed Forgetting Factor (SFFF)-RLS technique where the proposed method presented improved result with the future suggestion of temperature effect.

Table 2.4: Summary of the research papers for Filter based SOC estimation methods

Ref.	Algorithm	Functional	Result	Limitations
(Wassiliadis et al., 2018)	DEKF	MIL environment	DEKF shows better than EKF	Uncertainty of training and testing process
(Wang et al., 2018)	UKF	Series HEV	Error<1.5%	Experimental validation is required
(Shen, 2018)	AEKF	Pulsing and UDDS	For ISA, AAE is 2.43e-02	Inconsistency of early charge status for battery
(Zheng et al., 2018)	EKF+PF	DV analysis	MmAE=1.75%, RMSE<1.10%	Increment of battery lifetime
(Huang et al., 2018)	UKF+EKF	First order equivalent RC circuit model	Performance of MPSO is better than RLS	SOC falls accuracy for the incremental temperature
(Ramadan et al., 2017)	EKF	Second order equivalent circuit	Bo et al. (2015) did better performance than Watrin (2013)	Experimental validation is required
(Peng et al., 2017)	AUKF	Modified Sage Husa maximum posterior	RMSE 0.0163, MAE 0.0149	Experimental validation is required
(Zhao et al., 2018)	H _∞ EKF	NEDC-EV	Error≤2%	Inadequacy of battery lifetime affect increment of efficiency

Table 2.4 continued

(Liu et al., 2018)	AHIF- Δ OCV	DST & FUDS	Error is 0.11% (DST) & 0.18% (FUDS)	Experimental validation is required
(Xiong et al., 2017)	H infinity filter	Capacity & HPPC test	Error maxima 1%	Uncertainty of training and testing process
(Yu et al., 2017)	HIF-UKF	DST & UDDS test	At 40 °C, RMSE<0.5%, MAE<0.5%	Inaccuracy was noticed at large temperature
(Zhang et al., 2018)	DWRLS	Resistance & Capacitance	Accuracy nearly 1%	Increment of battery lifetime
(Wei et al., 2017)	RTLS	MADs	MAE 0.828% & 0.882%	Experimental validation is required

2.3.4 Model Based Estimation

The shortcomings of the direct SOC estimation method has been transcended by the Model based estimation. In this method, a battery model is set up with an advanced algorithm to establish the states of a battery from it's measuring factors for instance voltage, current, temperature etc. (Smith et al., 2010; Kim et al., 2012). Table 2.5 represents the summary of some research papers that contributed for the model based SOC estimation method. Several types of methodologies can be found from the literatures to estimate SOC unswervingly. But the electrical model and electrochemical model based State of Charge estimation has been reviewed in here owing to the fundamental scheme of the battery modeling (Klein et al., 2013; Eichi et al., 2014). These two types Model Based Estimation methods are described below:

i. Electrical circuit based method

In case of Electrical circuit based SOC estimation method, the battery model is considered mostly (Zou et al., 2014; Lin et al., 2015). A general calculation of the battery model was focused in (Zhang et al., 2017) where OCV was its open-circuit voltage, k was the number, I was current, T_s was sampling time in sec and C_n was the nominal capacity (Ah) of the battery model. The OCV and the SOC was established from Equation 2.29 and Equation 2.30 respectively,

$$OCV = f(SOC) \quad \text{Equation 2.29}$$

$$SOC(k) = SOC(k - 1) + I(k - 1) * \frac{T_s}{3600C_n} \quad \text{Equation 2.30}$$

Zhang et al. (2018) calculated the battery pack voltage and cell voltage separately (shown in Figure 2.14) and applied the dynamic voltage difference method on the ten series connected Li(NiCoMn)O₂ battery. In the experiment, 2.5% and 1% error was reduced at charging and discharging moment comparing to 2.8% and 1.5% error of pack model respectively. However, the model has to be verified for the practical validation.

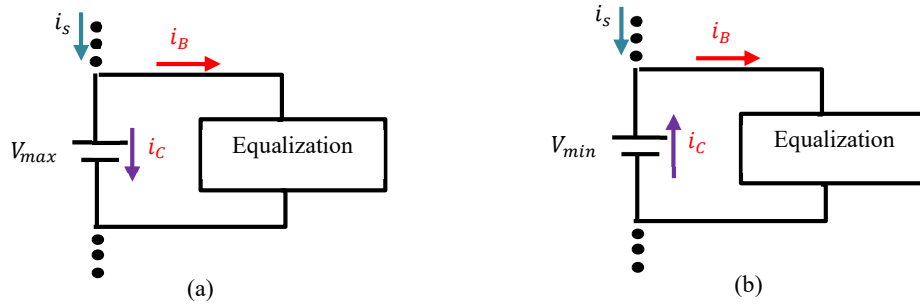


Figure 2.14: (a) V_{max} in charging procedure (b) V_{min} in discharging procedure (Zhang et al., 2018)

Wang et al. (2017) applied EKF-Ah algorithm for three different LIB models i.e. Thevenin, Partnership for a New Generation of Vehicles (PNGV) and Dual Polarization (DP) models for which the RMSE of the model error (%) and the SOC estimation error (%) was obtained according to the DST test was 0.2381, 0.0540, 0.1421 and 0.4365, 0, 0.4444 respectively. Both the Model error and the SOC estimation Error were tested with three kinds of tests named as Constant Current Discharge (CCD) test, HPPC test and DST test among which DST test was obtained effectively relating to others. Zhang et al. (2017) designed an electrical submodel and a thermal submodel where several temperatures were applied to appraise the internal heat generation as well as SOC estimation. The EKF algorithm was applied on the LiFePO₄ battery with the 2.31% estimated RMSE. Though the efficiency improved more than 20% by the investigated model, the aging effect and the temperature effect on the OCV was suggested as the future research.

ii. Electrochemical based SOC estimation

In case of SOC estimation by the Electrochemical model (EChM), diffusion, intercalation, electrochemical kinetics of a battery concerning equations are utilized. Since these types of equations are involved with the special familiarity of electrochemistry, for this reason their explanations are not mutual with the electrical and electronics engineering arena (Klein et al., 2013; Dey et al., 2015; Wang et al., 2015). As the time-varying stimulating partial differential equations are included in the Electrochemical model based SOC estimation, their implication for BMS is inflexible. Lotfi et al. (2017) observed the Electrochemical based SOC estimation for the LMO battery and verified it's robustness by the Lyapunov stability method. Though the MAPE for the UDDS and HWFET was achieved 0.2751% and 0.2910% respectively, the internal temperature fluctuations were occurred in case of the voltage model.

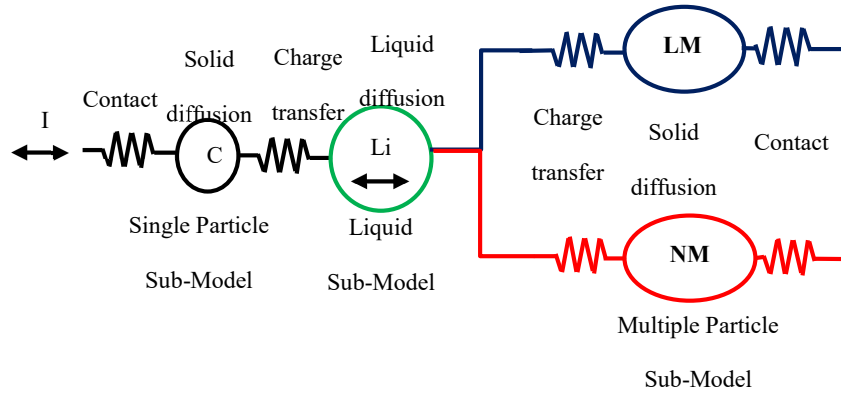


Figure 2.15: Schematic structure of the electrochemical model (Bartlett et al., 2013)

Table 2.5: Summary of the research papers for Model based SOC estimation methods

Ref.	Algorithm	Functional	Result	Limitations
(Zhang et al., 2018)	Dynamic Voltage	UDDS driving	Estimation error<0.3%	Experimental validation is required
(Wang et al., 2017)	EKF-Ah	cycle	RMSE for DP is 0.0540	Experimental validation is required
(Zhang et al., 2017)	EKF	CCD, HPPC & DST test	Estimated RMSE is 2.31%	Battery lifetime & temperature effect
(Lotfi et al., 2017)	Lyapunov stability	Electrical and Thermal submodel	MAPE was 0.2751% & 0.2910%	Uncertainty of training and testing process
(Bartlett et al., 2013)	Dual Observer	UDDS	At C/3, 25% SOC, error is 0.18 Ah	Increment of battery lifetime is required
(Corno et al., 2015)	EKF	& HWFET	Estimation error<5%	Error is high

H_2PbO_3 was utilized to estimate SOC for Lead-acid battery in (Pavlov 2017). The sealed LAB was mentioned as cheaper rather than other kinds of batteries such as NiCd and LIB. In this concern, 30% to 80% SOC containing LA battery was denoted in effective range neglecting the others. Dell et al. (2014) studied on battery and super-capacitor as storage

system for electric vehicle. PbSO_4 element was applied to guesstimate SOC from LA battery partially. The authors recommended BMS to improve the efficiency of the storage section by ranging 40% to 70% SOC of LA battery. The Partial Differential Equation (PDE) was used as a key function by Corno et al. (2015) where the EKF was applied on the LIB. Though the adeptness of the proposed model was improved (estimation error less than 5%) comparing to CFD model, the working out cost becomes high with the increment of subsystems.

2.4 PV-Battery Integrated System

Chettibi and Mellit (2018) proposed an intelligent control strategy for a grid connected hybrid energy generation system consisting of Photovoltaic (PV) panels, Fuel Cell (FC) stack and Battery Energy Storage System (BESS) in the Matlab/Simulink environment. An online-trained Elman Neural Network (ENN) based controller is developed to perform the tracking of the optimal operating point of the PV source. Moreover, a Takagi-Sugeno-Kang based fuzzy gain tuner is adopted for the adjustment of the PI parameters of the FC and BESS controllers. Besides, the Virtual Flux Oriented Control (VFOC) scheme based on neuro-fuzzy gain tuners is adopted to control the power flow between the hybrid system, the local loads and the utility grid. Furthermore, a centralized power supervisor is established to determine the levels of the power references for the local controllers according to the supply and demand conditions. The simulation results obtained demonstrate the efficiency of the proposed control scheme.

Abdelrazek and Kamalasan (2016) proposed a complete active-power management scheme for the control of Battery Energy Storage Systems (BESSs) for two main applications namely photovoltaic (PV) capacity firming and energy time shift (ETS).

The authors implemented two control algorithms to provide active-power set points to BESS for the above applications. An optimization routine for integrating these controllers is designed. The proposed approach uses an energy-conservation method to integrate the two applications of energy-storage system. The designed algorithm was tested on a transient simulation platform and then implemented on a 720-node actual power distribution feeder. The main advantage of the proposed method is that the algorithm can be used to optimize multiple functions and perform simultaneous control of BESS.

Natsheh and Albarbar (2012) studied on grid connected 28.8 kW PV-Battery integrated system in MATLAB/SIMULINK software by implementing P&O MPPT technique. The authors analyzed 21 month's period, using hourly average irradiance and cell temperature. The system showed power deviation (1.7 kW) between model prediction and actual power because of clouds, dust, snow cover and aging effect. Energy companies schedule the power supply in many developing countries where the energy supply capacity is less than the demand leading to grid scheduled blackouts (GSBs) for the costumers. Alramlawi et al. (2018) considered grid scheduled blackouts for optimal operation of PV-Battery hybrid system and calculated battery SOC to prolong the battery lifetime. Economic Model Predictive Control (EMPC) was applied to cover the maximum load and minimize the total cost of the energy consumption from the grid. The PV module was structured in (Abdel-Salam et al., 2018) as shown in Figure 2.16 where I_{SC} , I_D and I_{sh} symbolize to the short circuit current, diode (D) current and shunt current of resistance (R_{sh}). Moreover, I is the supply current of series resistance (R_s) and V is the load voltage.

Keshan et al. (2016) studied on off-grid energy storage systems and showed a comparison between lead-acid (LA) and lithium-ion battery. Though the lifespan of LIB is

high compared to LA battery, the economic cost is quite high in case of LIB. For instance, a LA battery pack costs around \$150 to \$200 per kWh where LIB partakes \$400 to \$700 per kWh. In this regard, the LA battery is cost effective rather than LIB.

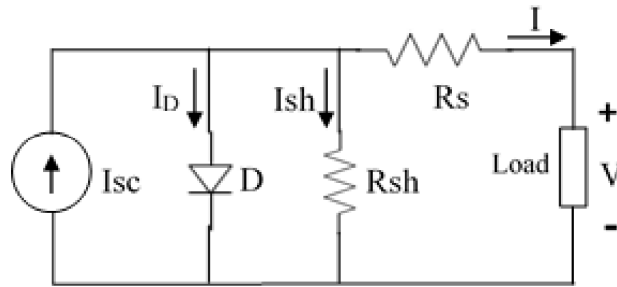


Figure 2.16: Single diode model of solar PV cell (Abdel-Salam et al., 2018)

The economics analysis of 140 Wp photovoltaic (PV) stand-alone system was inspected in (Anuphappharadorn et al., 2014) by showing the comparison between LA battery and LIB. In this concern, the initial investment cost for LIB was high as 39,930 baht where LA battery was only 17,010 baht. Furthermore, the benefit cost ratio for LIB was lower (0.13) than LA battery (0.19) that provides the priority for lead-acid battery solicitation.

May et al. (2018) reviewed the application of LA battery and depicted the peculiar comparison with LIB. In case of greenhouse gas emissions (CO_2), LA battery emits only 3 kg per unit which is extremely low rather than LIB as 12 kg/unit. Additionally, lead-acid battery possesses high recycling rates in full compliance with all environmental and other legislation rather than LIB. Furthermore, LIB contains high energy density and the organic electrolyte which is flammable as well as the thermal runaway is also risky. Hence, the authors supported the implementation of LA battery with respect to standalone storage system. Ohirul Qays et al. (2020) studied on charge regulation of LA battery by estimating

SOC through BPNN algorithm. The LA battery was investigated owing to its low cost installation for PV-Battery integrated system. In addition, 40% to 80% SOC containing battery was depicted in optimum range in this research.

2.5 Summary

This chapter was devoted to the presentation of the main work on the BMS based on SOC estimation technique for PV-Battery integrated system. Also, several algorithms for SOC estimation technique are reported in this chapter. From what has been exposed, it become evident that this study is a new area of research that is closely related to the application of BMS. Finally, the literature review was compiled, not to exhaust the subject on the large areas of system protection but aimed to show only some of the major works reported by techno-scientific community related to battery lifetime increment, as this research leads to that direction. So, after taking the review of all related works, it is found that, most of the problems in PV-Battery standalone system occur due to lack of synchronization or mal-operation of the energy storage system. However, the deficiencies in the above studies are covered in this study. Overall, the LA battery is preferable compared to other kinds of storage module in case of PV-Battery integrated system by keeping the SOC range between 40% to 80% safely. Hence, this study uses the advanced features of BMS along with the SOC estimation technique, which provides more efficient measurement and allows in lengthening the battery lifetime.

CHAPTER 3

METHODOLOGY

3.1 Chapter Overview

This chapter aims to represent the proposed methodology for the SOC estimation based BMS as well as all the tools and techniques used. It should be emphasized that all the theoretical and experimental contents covered in previous chapters, which elaborated the fundamental pillars for the development of the proposed methodology, provide imperative information about the state of the art of literature of BMS, SOC estimation, control structure respectively.

The literature review endorsed us to observe the techniques developed for SOC estimation areas of the system under discussion through BMS. In relation to their respective algorithms, the development of the SOC estimation model is designed to monitor and protect the battery from damages. The control technique is capable of fetching the inputs from battery parameters and proceeding to the battery model properly. Besides, the simulation model prepared from MATLAB/SIMULINK and experimental model analysed in dSPACE1104 are constructed in in this chapter. Flowchart for the entire simulation and experimental system is shown in Figure 3.1. Firstly, the simulation process of PV, battery, load and controlling sector is completed in the aforementioned software. After succeeding the simulated design, the analogous model is interpreted with the hardware prototype. According to the processed outcome of the numerical model, the experimental elements are commanded from the BMS headed for accomplishing the essential actions through the data acquisition. Overall, the projected methodology is organized in this chapter as follows:

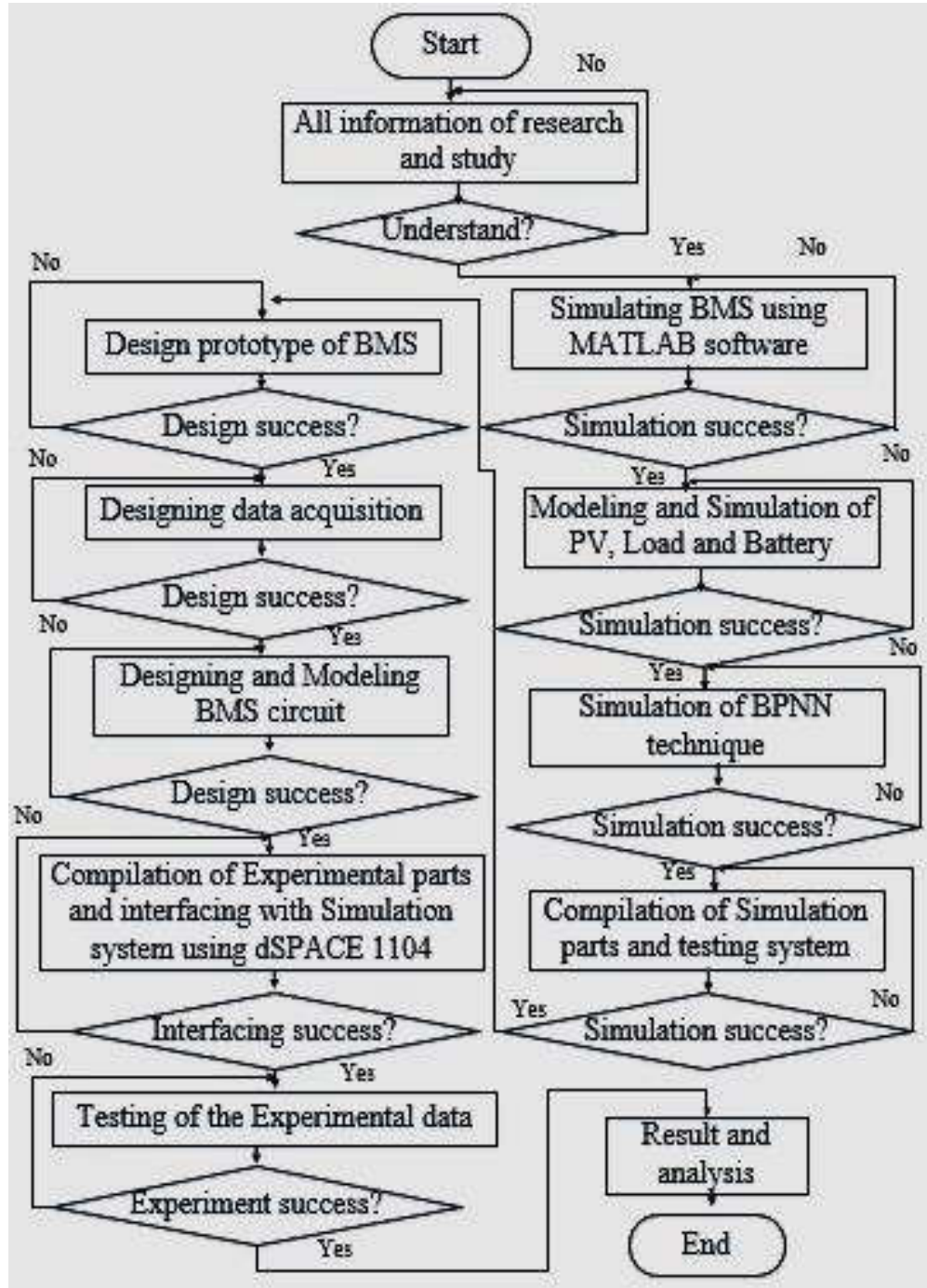


Figure 3.1: Flowchart for the entire system

Section 3.1 overviews the chapter with description of the projected simulation model. The PV module, battery model, MPPT is described in Subsection 3.2.1, Subsection 3.2.2 and Subsection 3.2.3 respectively. Section 3.3 provides the physical prototype of the experimental model. Various types of components e.g. dSPACE1104, Solar PV module,

SMNT Battery, Voltage/Current sensors are described in different subsections accordingly. And finally the chapter is summarized by Section 3.4.

3.2 Modeling and Simulation

3.2.1 Photovoltaic (PV) Model

The equivalent circuit model of single diode PV cell is portrayed in Figure 2.16. It consists of several parameters such as a current source I_{sc} , a series resistance R_s , a shunt resistance R_{sh} , diode current I_D , reverse saturation current I_0 shunt resistance current I_{sh} , terminal/load voltage V and PV cell power P (Bendib et al., 2015; Castro, 2018). The circuit is not restricted only for a PV cell structure, any composite multicell system for instance a PV module, string, or array can be operated under uniform conditions. The current–voltage equation of the model is depicted from Equation 3.1 to Equation 3.3.

$$I_D = I_0 \left[\exp\left(\frac{V+IR_s}{nV_T}\right) - 1 \right] \quad \text{Equation 3.1}$$

$$V_{OC} = \frac{KT}{q} \ln\left(\frac{I_{SC}}{I_0} + 1\right) \quad \text{Equation 3.2}$$

$$P = V * I = VI_{SC} - VI_0 \left[\exp\left(\frac{V+IR_s}{nV_T}\right) - 1 \right] \quad \text{Equation 3.3}$$

Where q , K and T are the electron charge ($1.60217657 \times 10^{-19}$), Boltzmann constant ($1.3806488 \times 10^{-23}$) and module temperature respectively, $V_T = \frac{KT}{q}$ is the thermal voltage. A more truthful equation for V-I characteristics of solar cell is clarified for the supply current I in Equation 3.4 and Equation 3.5 as a result of considering the internal series and parallel resistance losses R_s and R_p correspondingly.

$$I = I_{SC} - I_D - I_{sh} \quad \text{Equation 3.4}$$

$$I = I_{SC} - I_0 \left[\exp\left(\frac{V+IR_S}{nV_T}\right) - 1 \right] - \left(\frac{V(1+R_{Sh})}{R_p}\right) \quad \text{Equation 3.5}$$

3.2.2 Battery Model

Battery model is exercised to conduct the affiliation between internal and external performance of a battery. Generally two types of battery models are classified namely electrochemical model and equivalent circuit model. Electrochemical model entirely depends on internal chemical reaction of a battery that contains analytical complexity and calculation delinquencies to achieve parameter accurateness. On the other hand, equivalent circuit model relies on external dynamic appearances that can sidestep the comprehensive deviousness of internal electrochemical progressions (Orchard et al., 2015; Cui et al., 2018). Therefore, Equivalent circuit model is frequently enrolled to replicate the cells' peripheral characteristics and enhance the truthfulness of BMS. In addition, a first order Thevenin Equivalent circuit model which is shown in Figure 2.1 can be demonstrated from Equation 3.6; V_{OC} is open circuit voltage (OCV), C_p is parallel capacitance, R_s and R_p are series and parallel resistance respectively; $i_p = V_p/R_p$.

$$V_L = V_{OC} + i * R_s + \int \frac{i - i_p}{C_p} dt \quad \text{Equation 3.6}$$

3.2.3 MPPT

Perturb and Observe (P&O) is the most popular and widely implemented Maximum Power Point Tracking (MPPT) technique owing to its simplicity of application and individuality of PV array parameters. The working principle of P&O is explained by the flowchart in Figure 3.2. This is an incessant procedure of observation and perturbation until the working point meets to the MPP as reported by Abdel-Salam et al. (2018). The algorithm compares the time (K) of the PV power and voltages with the sample time (K-1) and foresees the time of MPP.

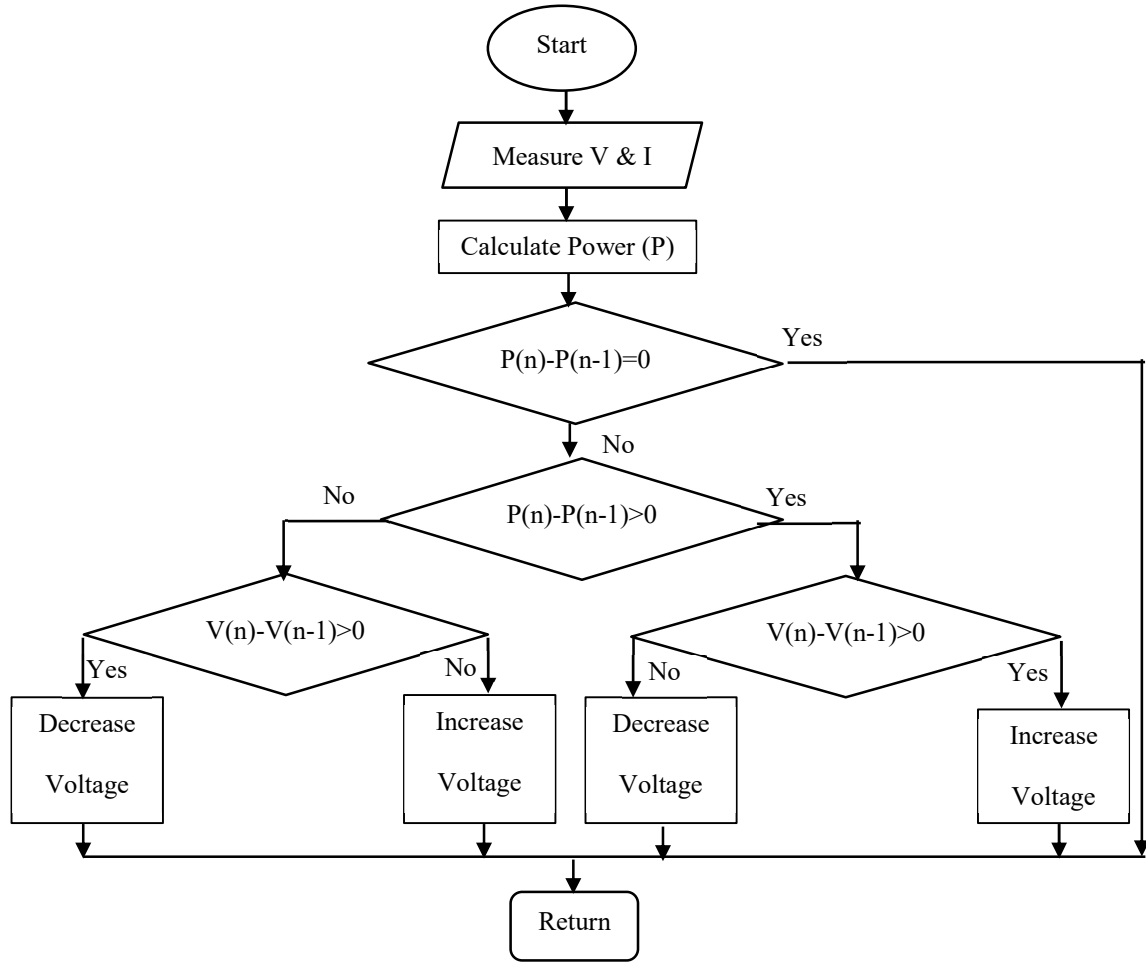


Figure 3.2: Flowchart for P&O MPPT algorithm

If the power alteration is positive, a small voltage perturbation is increased to change the power of the solar panel. Moreover, if the voltage of a certain moment $V(n)$ is larger than the previous moment $V(n-1)$, the voltage is further increased and vice-versa. Conversely, the negative delta power indicates that the MPP is far away from the operating point and so the voltage perturbation is reduced to reach the MPP. In this concern, if the voltage of a certain moment $V(n)$ is larger than the previous moment $V(n-1)$, the voltage is further decreased, otherwise it reverts. Hence, the entire PV curve is checked in this way by small perturbations to find the MPP that upturns the response time of the algorithm.

3.2.4 BPNN

The implication of SOC estimation accuracy is remarkable for Lead-Acid battery to certify its safety maneuver and avoid from over-charging or deep-discharging factors. Nonetheless, SOC estimation is a challenging issue for the battery bank owing to its nonlinear electrochemical reactions according to Cao et al. (2017). In this research, BPNN based SOC estimation algorithm is employed for which the structural design of the procedure is shown in Figure 3.3 (Hannan et al., 2018). The proposed model collects two parameters: voltage and current from the battery in addition to estimate SOC bestowing the equations from Equation 3.7 to Equation 3.13. Weights are adjusted according to the Root Mean Square Error (RMSE) of the SOC estimation in an attempt to construe the assessed-outcomes more accurately. The total input of a hidden layer neuron can be reflected from Equation 3.7 considerably.

$$neti_n = \sum_{i=1}^3 x_i w_{in} + b_n \quad \text{Equation 3.7}$$

Where, $neti_n$ is total input of the hidden layer neuron n , x_i is the value of input neuron to hidden layer neuron n , w_{in} is weight between input layer neuron i and hidden layer neuron n , b_n is the bias of the hidden layer neuron n . The hidden hidden layer neuron h_n and output $neto$ can be calculated from Equation 3.8 and Equation 3.9 respectively.

$$h_n = f(neti_n) = \frac{1 - \exp(-2neti_n)}{1 + \exp(-2neti_n)} \quad \text{Equation 3.8}$$

$$neto = \sum_{i=1}^n h_i g_i + p \quad \text{Equation 3.9}$$

Here, $neto$ is total input of the output layer neuron o , h_i is the value of hidden layer neuron to output layer neuron i , g_i is the weight between hidden layer neuron i and output layer neuron o , p is the bias of the output layer neuron o . In the output layer neuron, the

applied activation function is the sigmoid function. Output y_n can be calculated from Equation 3.10.

$$y_n = f(neto) = \frac{1}{1+\exp(neto)} \quad \text{Equation 3.10}$$

The error is calculated Equation 3.11. To obtain the desired output and reduce the error, the weights are updated repeatedly by gradient descent Equation 3.12 to Equation 3.13. The optimized weights are acquired when the error is minimized.

$$RMSE = \sqrt{(\sum_{i=1}^n e_i^2)/n} \quad \text{Equation 3.11}$$

$$e_i = f_{Ref} - f_{Est} \quad \text{Equation 3.12}$$

$$\frac{\partial Error}{\partial w_{ij}^n} = \frac{\partial Error}{\partial f_{Est}} \frac{\partial f_{Est}}{\partial w_{ij}^n} \quad \text{Equation 3.13}$$

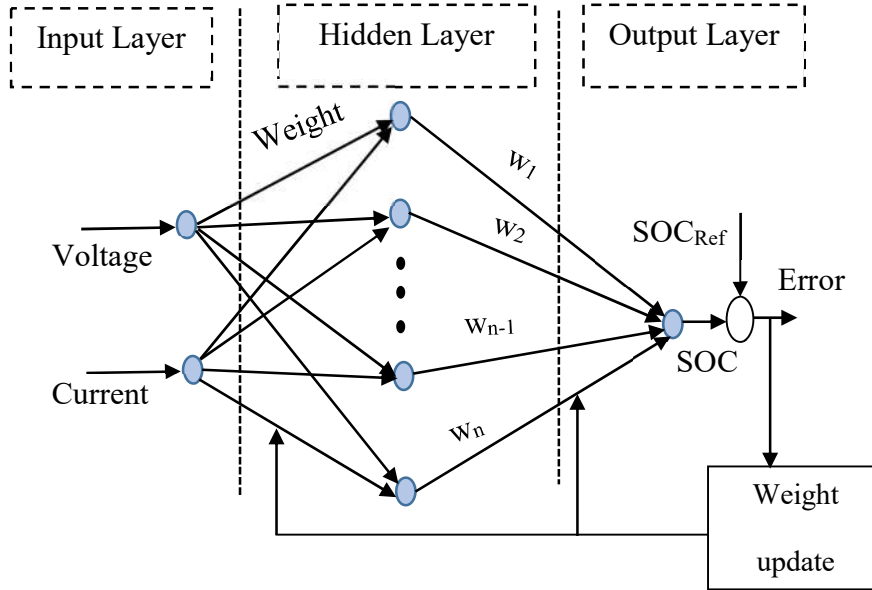


Figure 3.3: Structure of BPNN algorithm

The algorithm is fixed in MATLAB/SIMULINK 2019a software. The collected data (voltage and current) is analyzed with the Artificial Neural Network Toolbox. It generates a NNET model (shown in Figure 3.4) that receives the battery parameters and estimates SOC. The BPNN simulation code and NNET toolbox model as shown in Figure 3.4 refers to

Appendix B. In case of simulation model, the NNET block acts similar to the real world particular battery (12 V, 7 Ah). The training and testing data is obtained by charging and discharging the acquired data frequently. Consequently, the entire simulation model can be worked as the real life application successfully.

3.2.5 Simulated Model

With the aim of validating the usefulness of the anticipated BMS, the proposed model is simulated in the Matlab/Simulink environment as shown in Figure 3.5. To avoid system complexity of this paper, BMS governs the MPPT scheme and SOC produced from the PV panel and battery bank respectively. Typically, BMS continues the model with two dynamic approaches: (1) MPPT and (2) SOC estimation as shown in Figure 3.6. Under any condition of solar radiation and ambient temperature, PV panels are operated at MPPT scheme to generate maximum possible power with the available insolation. Oppositely, battery SOC is estimated with the help of BPNN technique as well through receiving the battery parameters. Since this research focuses on battery charge status primarily, the control technique verifies the estimated SOC with collaborating PV supply and load demand. If PV supply can support the load demand properly, battery section is kept in islanding mode to reduce its utilization. Furthermore, the battery section will be charged or discharged by following the PV supply involvement.

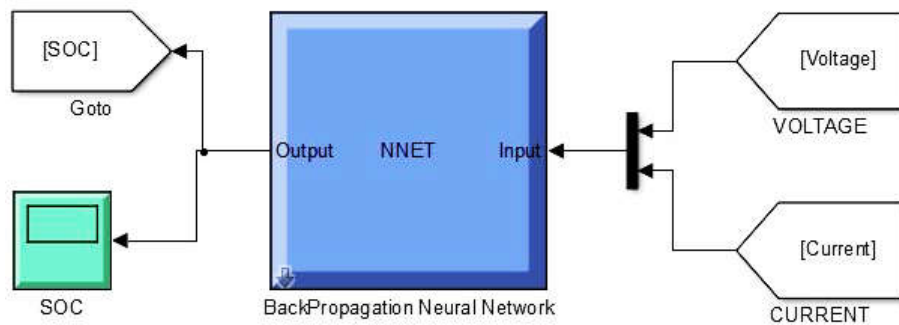


Figure 3.4: NNET model in SIMULINK

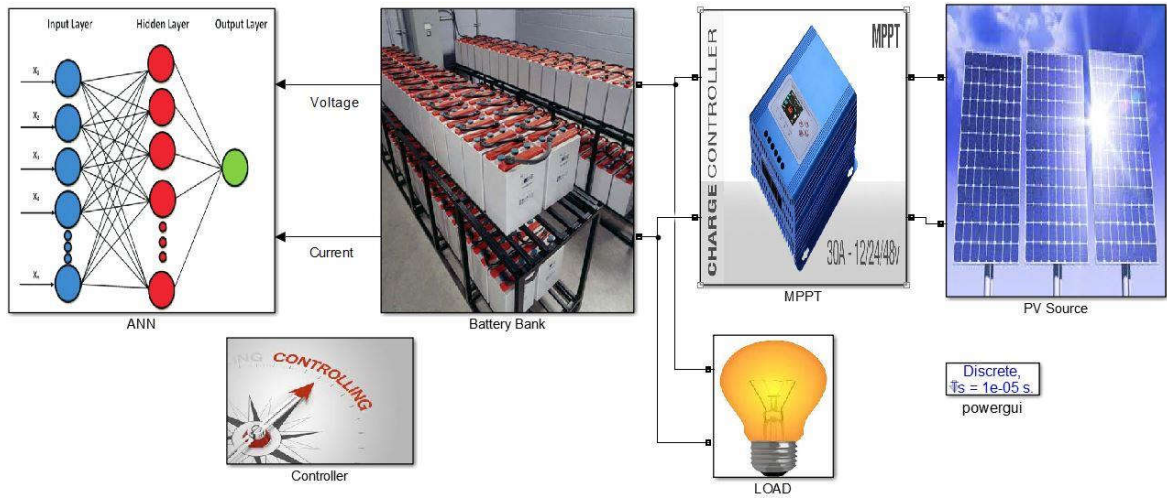


Figure 3.5: Simulink structure of the projected model

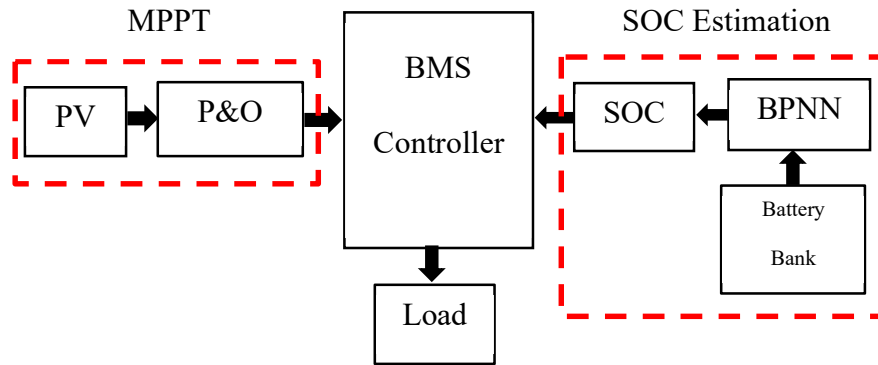


Figure 3.6: Schematic diagram of the projected model

The simulation is completed by collecting the data from Renewable Energy Lab, UNIMAS which are referred in Appendix A. In this project, 48 V, 300 Ah HOPPECKE solar.bloc Lead-Acid battery is installed with 3.5 kW NT175E1 PV ($V_{OC}=44$ V, $I_{SC}=5.4$ A, $P_m=175$ W) solar system as shown in Figure 3.7. The load was fixed as 2000 W or 2kW. The real-time data is saved into a memory component from which it was collected to complete the simulation design. The successful BMS control strategy lead the proposed model in the direction of applying into the experimental setup. In this concern, the entire flowchart of the planned BMS control technique is shown in Figure 3.8 where the working procedure of BMS

controlling scheme is deliberated by involving the PV power generation, load demand and battery storage capacity. Firstly, the BMS estimates SOC by gathering the battery voltage and current data. The PV supply power and load demand is also checked in this duration. If the power generation is similar to the load demand, it is kept in the islanding mode. Conversely, the battery is in charging mode if the PV supply can facilitate the load demand along with the battery section. In addition, the battery is in discharging mode if the PV supply can not facilitate the load demand and so the battery section has to discharge it's charge status. In this regard, the SOC range is limited between 40% to 80%. Beyond of 80% and below 40%, the battery sector is brought about in islanding mode headed for avoiding the over-charging and deep-discharging issues respectively.



(a)



(b)

Figure 3.7: (a) Combined Solar Panel (b) System Controlling Room

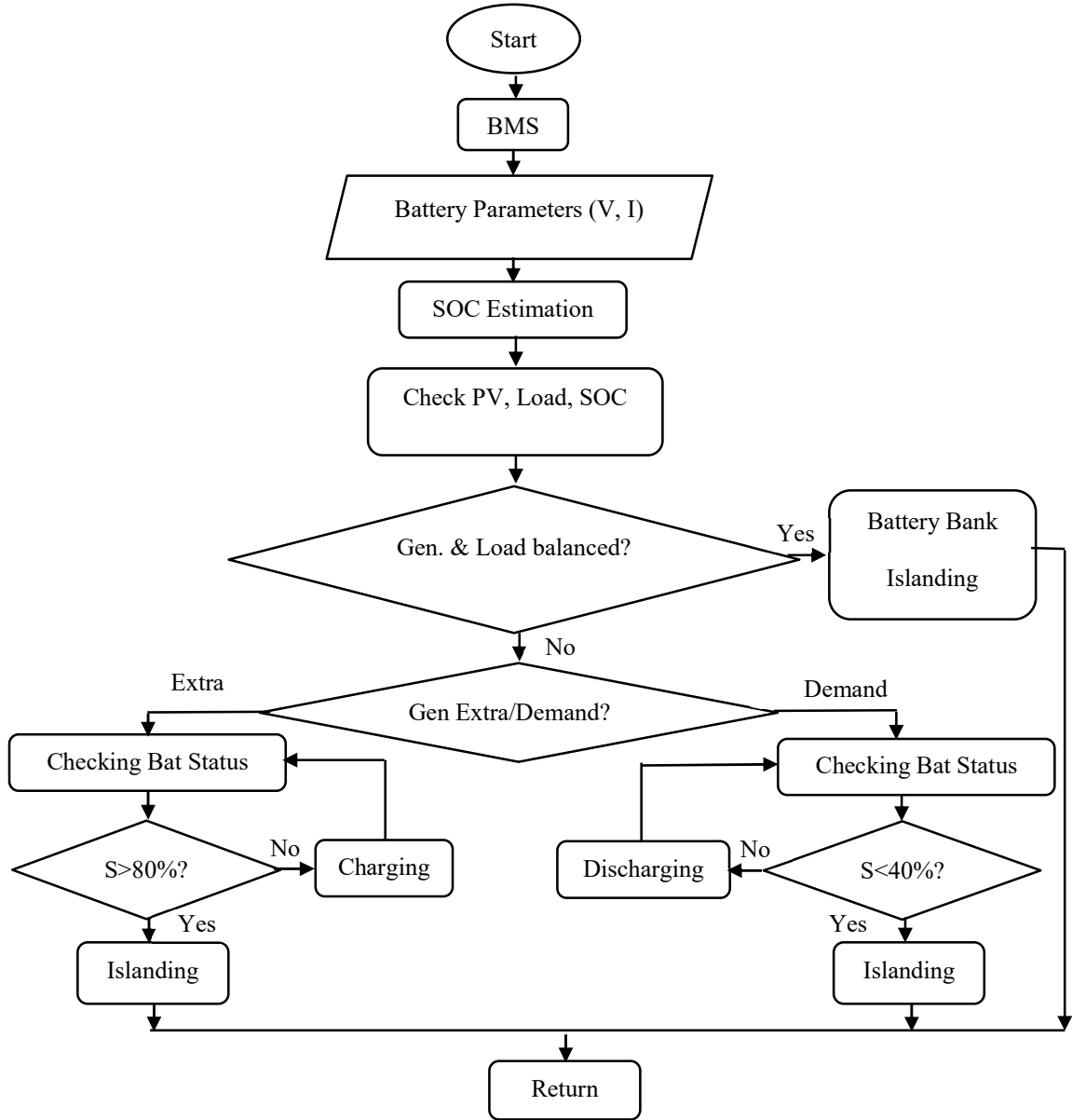


Figure 3.8: Flowchart of the BMS controlling technique (Qays et al., 2019)

3.3 Experimental Design

3.3.1 Hardware controller

dSPACE software packages Control desk:

- It is a graphical user interface for managing the dSPACE boards, in addition to the functions of managing experiments via the experiment manager and offering

variety of virtual instruments to build and configure user interface for the application.

- The dSPACE real-time library
Real-time library includes all blocks necessary for implementation of models in real-time.

Hardware of dSPACE controller:

- a. The dSPACE1104 card controller board is a single-board system. The hardware package contains:

One PCI-slot board with a bracket including a 100-pin I/O connector and

One adaptor cable with two 50-pin female Sub-D connectors

- b. The dspace1104 R&D system contains different parts such as:

- The dSPACE 1104 R&D controller board:

This board is a standard board that can be plugged into a PCI slot of a PC. It is a complete real-time control system based on a 603 PowerPC floating-point processor running at 250 MHz. For advanced I/O purposes, the board includes a slave-DSP subsystem based on the TMS320F240 DSP microcontroller. The block diagram of the dSPACE 1104 board R&D is shown in Figure 3.9.

- Adaptor cable with sub-D connectors:

Using the adaptor cable we can link our external signals from the 100-pin I/O connector on the board to sub-D connectors connected with connector LED panel (CLP 1104) that used for accessing all signals on the board hardware.

- 3-CLP1104:

The panel board of dSPACE 1104 is shown in Figure 3.10 that is used for receiving or sending signals. The analog signal can be received as a digital signal via input port ADC1 to ADC8. Furthermore, DAC1 to DAC8 can be used to send the digital signal as the analog output.

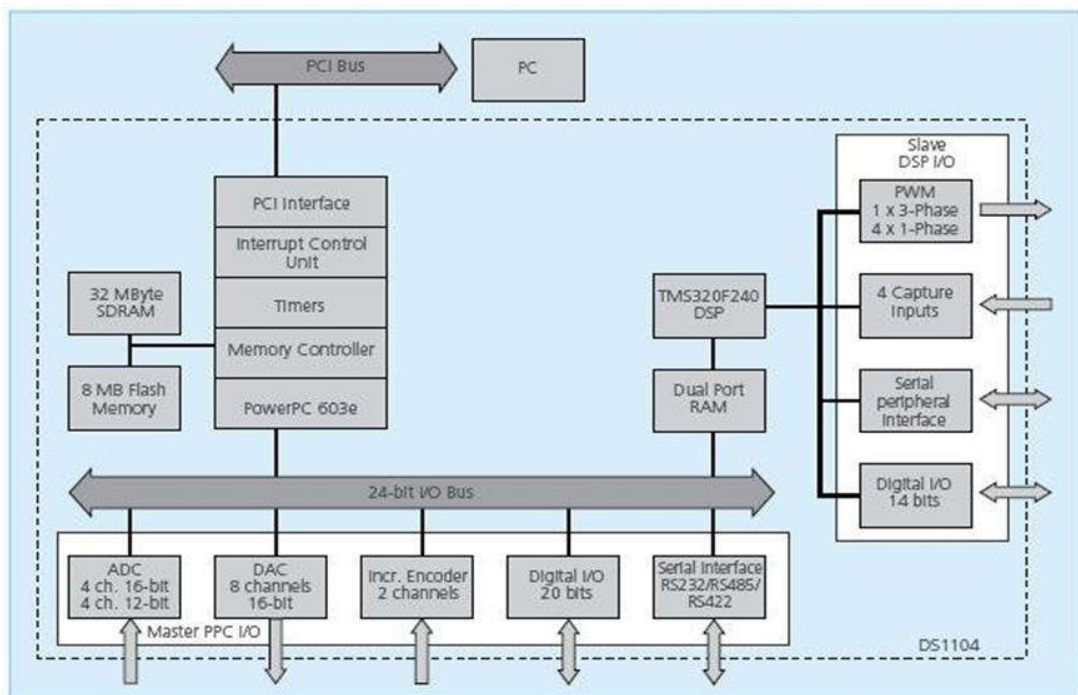


Figure 3.9: Block diagram of the dSPACE 1104 R&D system hardware

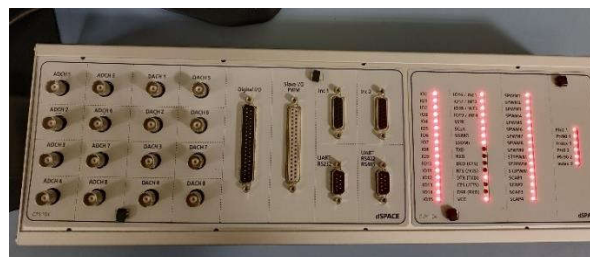


Figure 3.10: CLP1104 I/O board

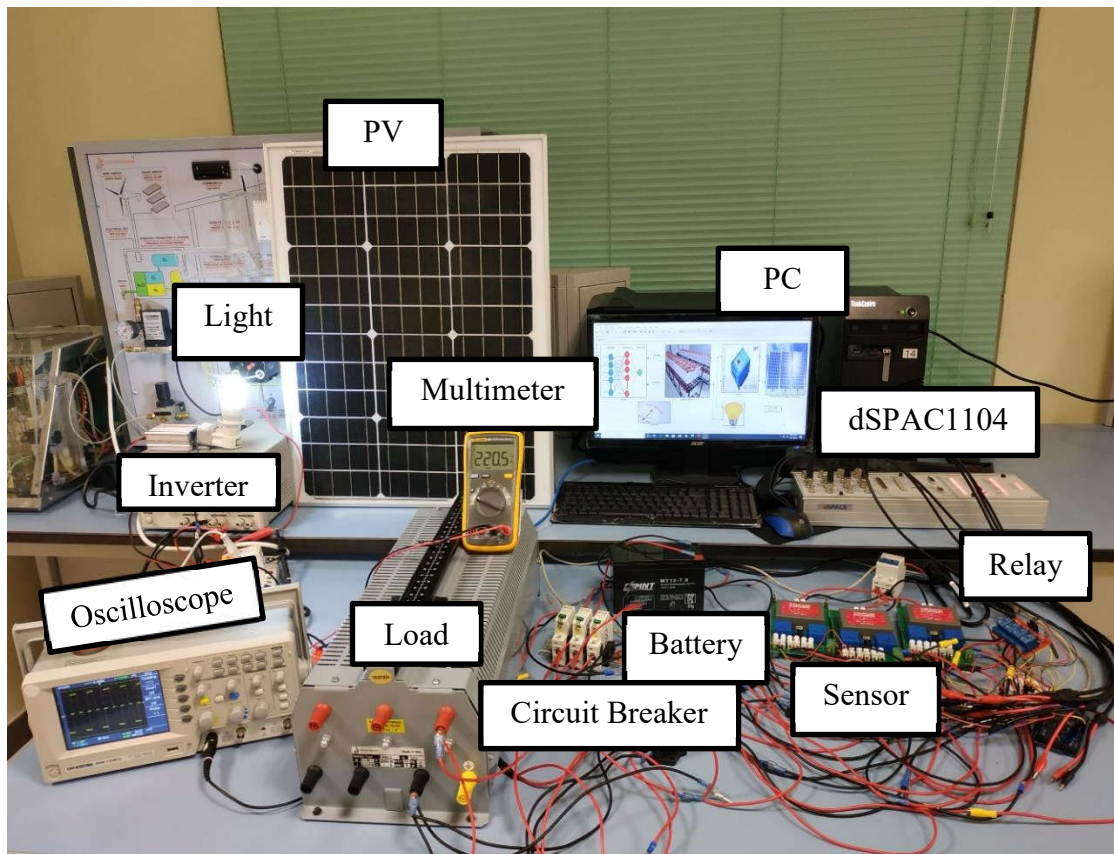


Figure 3.11: Experimental setup of the projected model

3.4 Experimented Prototype

A physical prototype (shown in Figure 3.11 and Appendix C) of the proposed model is designed in the laboratory environment. The PV panel is kept in the outside atmosphere to measure the solar irradiance and temperature significantly. Here, the PV solar panel, battery and loads are connected through fuse and circuit breaker. A Line Diagram of the projected circuit is shown in Figure 3.12. MATLAB/SIMULINK 2019a is interfaced with dSPACE 1104 controller. The integration of MATLAB Tools for dSPACE Code Generation block diagram is shown in Figure 3.13. The voltage and current sensors sense the voltage and current from the corresponding element (shown in Figure 3.14) and provides the signal to the designed PC model through dSPACE1104. The SIMULINK model analyzes the data

and estimates PV power, Battery SOC and load power. Since, the aim of this project is to monitor the battery system management, by following the condition of the control system, BMS commands the relay switches to charge, discharge or island the battery section.

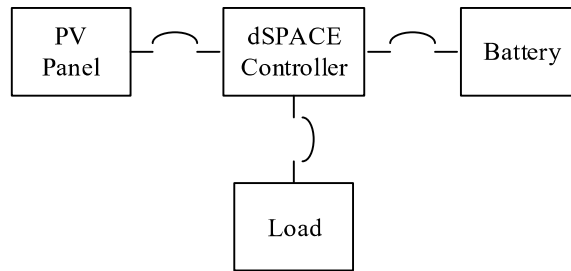


Figure 3.12: Line Diagram of the projected circuit

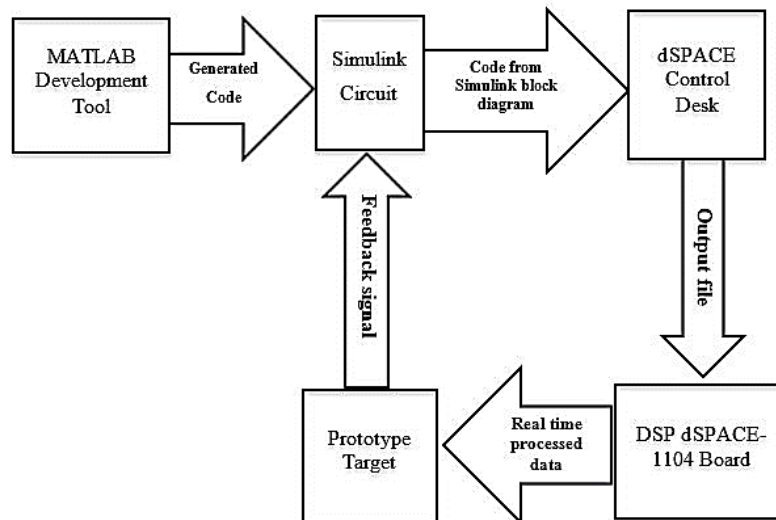


Figure 3.13: Integration of MATLAB Tools for dSPACE Code Generation block diagram

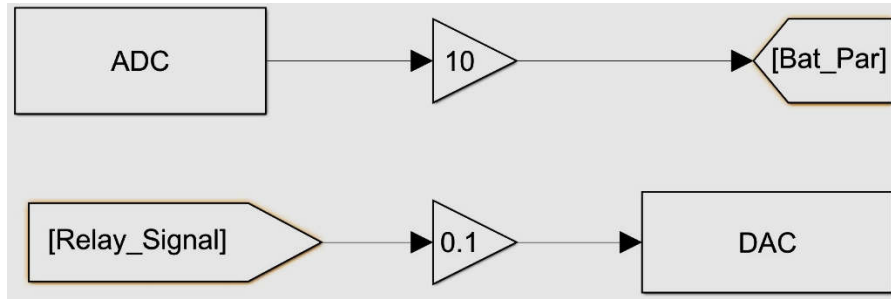


Figure 3.14: ADC and DAC signal provided in SIMULINK

3.5 Summary

This chapter clarified and demonstrated the proposed methodology with the developments made to the simulation and experimentation model of BMS. The numerical and experimental methodology is described in this chapter where some complexities were noticed uncertainly compared to other authors. For instance, the low qualified data were stranded owing to the fluctuation of atmospheric conditions. Afterwards, a little bit noisy was included in the voltage or current signal due to the poor quality of instruments. Therefore, the simulated and experimental models were examined consciously so that the objectives could be met up fruitfully.

Furthermore, due to reduce the complication of the projected model, this study used three standard modes for battery storage section to check the robustness of the projected methodology, which are islanding mode, charging mode and discharging mode. The results for verification of robustness of the proposed methodology are given for the four cases in Chapter 4.

CHAPTER 4

RESULTS AND DISCUSSION

4.1 Chapter Overview

Several programs are available to the researchers of the power electronics area for BMS such as OCV, SOC, SOH etc. Moreover, different types of software e.g. Python, MATLAB/SIMULINK, Microtan, Java and hardware e.g. Arduino, dSPACE, Texas Instrument, National DAQ are available to have a proper control system. Though these, by computer simulations, it is possible to make the correct modeling of a given BMS that will allow the accumulation of data close to the actual, found in the field.

This study has opted for the use of MATLAB/ SIMULINK 2019a and dSPACE 1104 interfacing platform which features a friendly graphical user interface, providing the user with the possibility of programming by blocks, and with an interface of Sim-Power system environment, thereby facilitating the interaction with the system modeling. Through its interface, the basic components such as loads, power source etc. can easily be included on modelled according to the users' necessity. More information can be found in the manual of MATLAB-dSPACE sections. This chapter is organized as:

The simulation results of the proposed model are given in Section 4.2. Different types of case study such as charging, discharging, islanding mode, pure AC voltage production, modified AC voltage production is described in the subsections respectively. Section 4.3 describes the experimental results of the physical prototype by following to the simulation resultants. Afterwards validation of the proposed methodology is detailed through the

conventional and projected model in Section 4.3. Lastly, the summary of the work is given in Section 4.4.

4.2 Simulation Results

Though battery SOC can be varied from 0% to 100% at charging/discharging mode, in case of removing the overcharging/deep discharging of the storage system, 40% to 80% SOC is considered as an operating charge status for battery bank. BMS compares the estimated SOC with the reference SOC continuously as well as takes decision about the battery bank charging, discharging or islanding mode. Independently, four working days were investigated (March-April, 2018) from Renewable Energy Lab of Universiti Malaysia Sarawak that is mentioned in Figure 4.1 to Figure 4.4. Though the lithium-ion battery is maintenance free and contains high lifespan, the installation cost and greenhouse gas emission of lead-acid battery is extremely low. Moreover from the literature review, 40% to 80% SOC containing lead-acid battery can perform its activities effectively. Hence, sealed lead-acid battery is applied in this research by limiting the SOC into aforementioned range. Additionally by following the manufacturing information, the battery temperature is carried out constant as 25 °C.

4.2.1 Case 1

On the first day, 80% SOC containing battery was verified at 1100 W/m² solar irradiance and 33 °C temperature to examine the condition. Nearly 2800 W sufficient power was supplied from PV supply at 58.33 A charging rate to the load demand on that day. Since the battery was contented with maximum SOC, to safeguard the battery bank from over-

charging issue, the storage system was resulted in the islanding mode as shown in Figure 4.1.

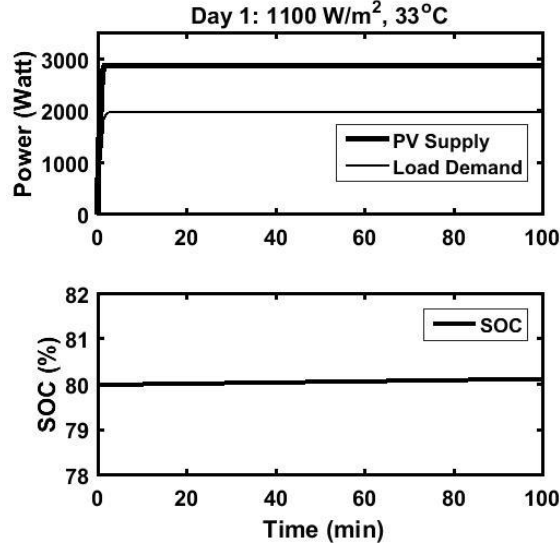


Figure 4.1: Simulation analysis for Day 1: 1100 W/m², 33 °C

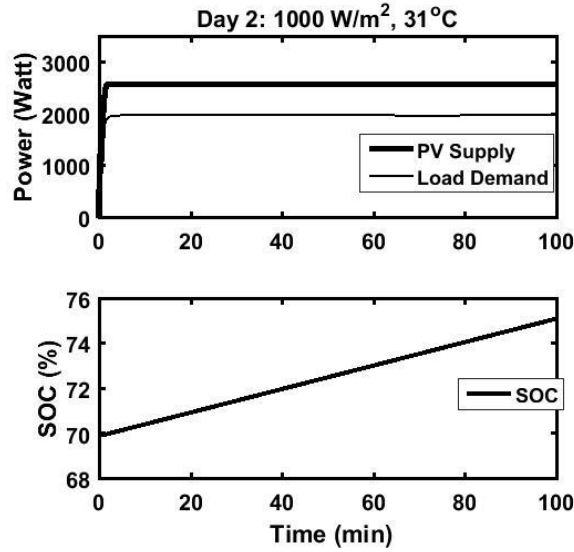


Figure 4.2: Simulation analysis Day 2: 1000 W/m², 31 °C

4.2.2 Case 2

In the second day of 1000 W/m² irradiance 31°C temperature, 70% SOC comprising battery was investigated that brought about the charging mode. Because the PV system was adequate (nearly 2500 W) at 52.08 Ah charging rate to deliver the load demand and charge the battery bank satisfactorily as shown in Figure 4.2.

4.2.3 Case 3

Furthermore on the 3rd day, the project was carried out in 50% SOC, 800 W/m² irradiance 27 °C temperature. On that day, PV supply (nearly 1700 W) was insufficient to support the load demand. And so, the battery bank was resulted in the discharging mode at 35.42 Ah discharging rate headed for covering the load demand as shown in Figure 4.3.

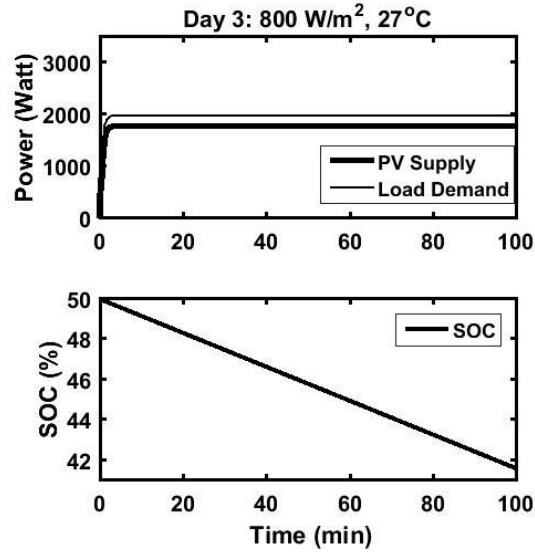


Figure 4.3: Simulation analysis for Day 3: 800 W/m², 27 °C

4.2.4 Case 4

Lastly, the BMS is analysed for 40% SOC battery charge status with 600 W/m² irradiance 23 °C temperature. From Figure 4.4, the situation of the 4th day can be described appropriately. In this day at 20.83 Ah discharging rate, the PV supply cannot meet the load demand as well as the battery charge level is reached for the safest minimum states to support the capacity. Hence, BMS stopped the load file to prolong the battery life from Deep of Discharge (DOD).

4.2.5 AC Voltage

To improve the research qualification of this novel research and implement in the industrial application successfully, 230 V, 50 Hz AC supply is produced as shown in Figure 4.5. The details of the produced AC voltage as well as AC sine wave are given below:

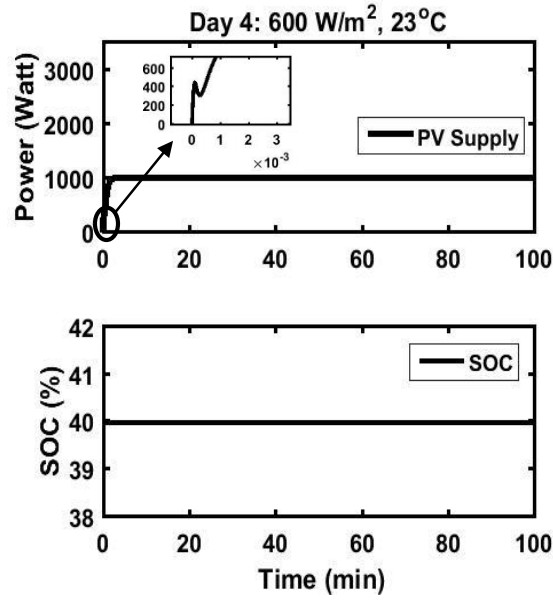


Figure 4.4: Simulation analysis for Day 4: 600 W/m², 23 °C

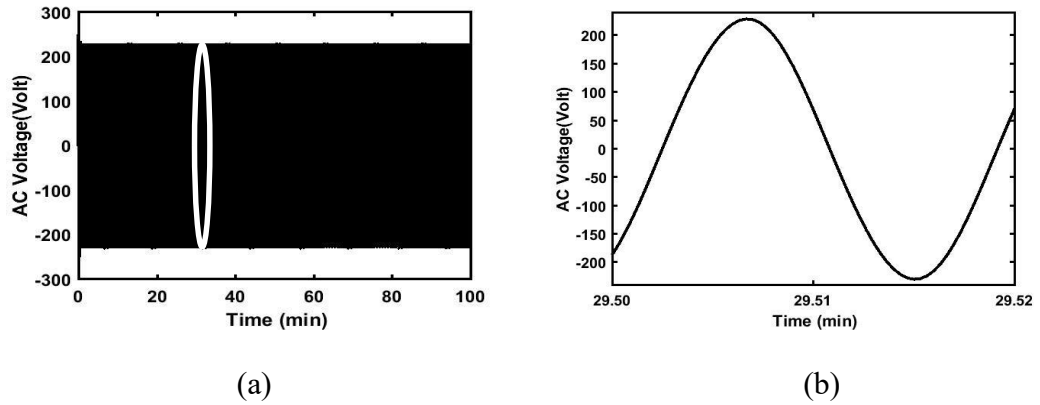


Figure 4.5: AC Voltage (a) Density (b) Pure Sine wave for a particular moment

i. Pure Sine Wave

To improve the application facility of the research production, PV DC/DC voltage was converted into 230 V, 50 Hz AC supply that is shown in Figure 4.5. Figure 4.5 (a) expresses the density of the system AC voltage and Figure 4.5 (b) indicates the creation of pure AC voltage (sine wave) in a certain time range (29.50 min-31.00 min).

ii. Modified AC Sine Wave

The primary job of an inverter is to convert the DC (Direct Current) power from the battery bank or solar panels to AC (Alternating Current) power needed for most appliances. To do that, it must take the constant DC voltage and change it to a sine wave curve that goes above and below zero volts. Modified sine wave inverters are a cost effective choice to run appliances and equipment that is less sensitive to power fluctuations, such as lights and low powered uses. And so, from the simulating model, the modified sine wave is generated for the industrial application. Figure 4.6 shows 230 V, 50 Hz modified AC Sine Wave which is generated by simulation.

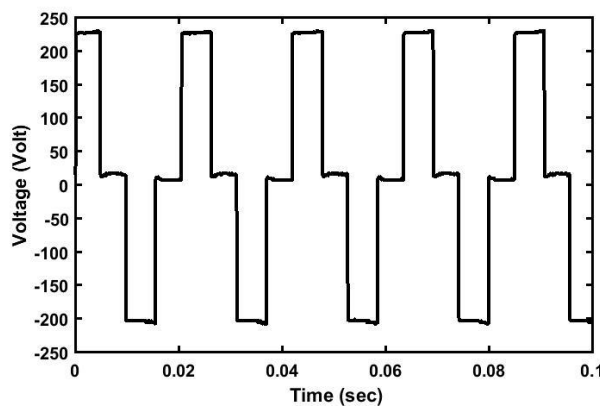


Figure 4.6: Modified AC Sine Wave by simulation

4.3 Experimental Results

4.3.1 Case 1

Firstly, 80% SOC containing battery was tested in 620 W/m^2 solar radiation and 29°C temperature to investigate the situation. On this day, since sufficient power (nearly 10.8 W) was provided from PV supply to the load demand at 0.92 Ah charging rate and battery was contented with the maximum SOC suitably, the storage system was resulted in the islanding mode to protect the battery bank from over-charging factor as shown in Figure 4.7.

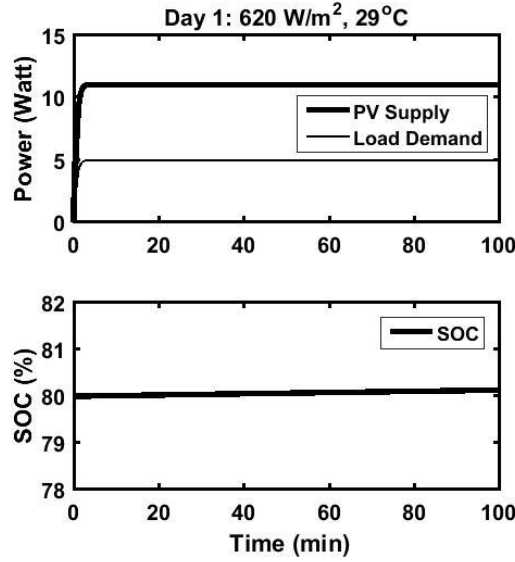


Figure 4.7: Experimental analysis for Day 1: 620 W/m^2 , 29°C

4.3.2 Case 2

In the second day of 540 W/m^2 irradiance 27°C temperature, 65% SOC comprising battery was investigated that brought about the charging mode. Because the PV system was adequate (nearly 8.2 W) to deliver the load demand by 0.68 Ah charging rate and charge the battery bank satisfactorily as shown in Figure 4.8.

4.3.3 Case 3

Furthermore on the 3rd day, the project was carried out in 55% SOC, 372 W/m² irradiance 23 °C temperature. On that day, PV supply (nearly 3.8 W) was insufficient to support the load demand. And so, the battery bank was resulted in the discharging mode at 0.32 Ah discharging rate headed for covering the load demand as shown in Figure 4.9.

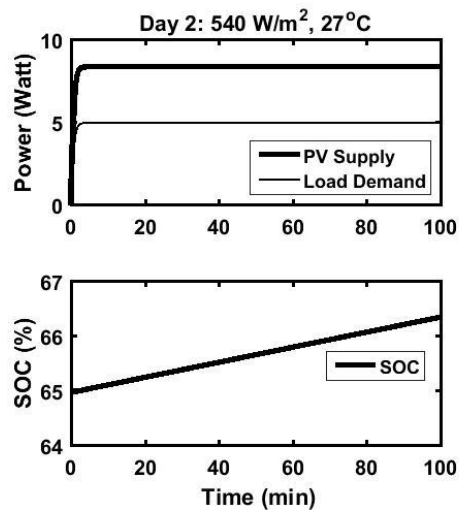


Figure 4.8: Experimental analysis for Day 2: 540 W/m², 27 °C

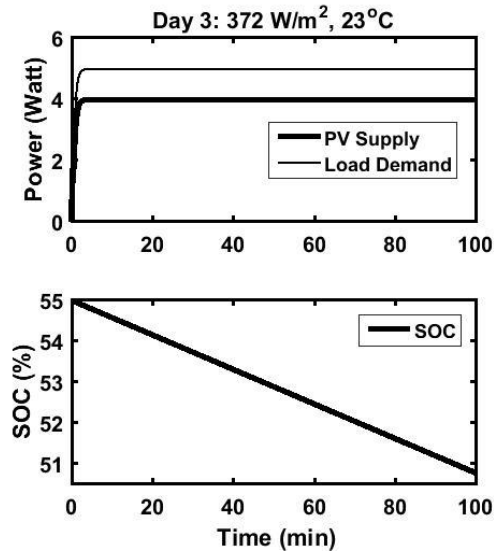


Figure 4.9: Experimental analysis for Day 3: 372 W/m², 23 °C

4.3.4 Case 4

Lastly, the BMS is analyzed for 40% SOC battery charge status with 322 W/m^2 irradiance 21°C temperature. From Figure 4.10, the situation of the 4th day can be described appropriately. In this day, the PV supply (2.9 W with 0.24 Ah discharging rate) cannot meet the load demand as well as the battery charge level is reached for the safest minimum states to support the capacity. Hence, BMS stopped the load file to prolong the battery life and extend the working function from deeper Depth of Discharge.

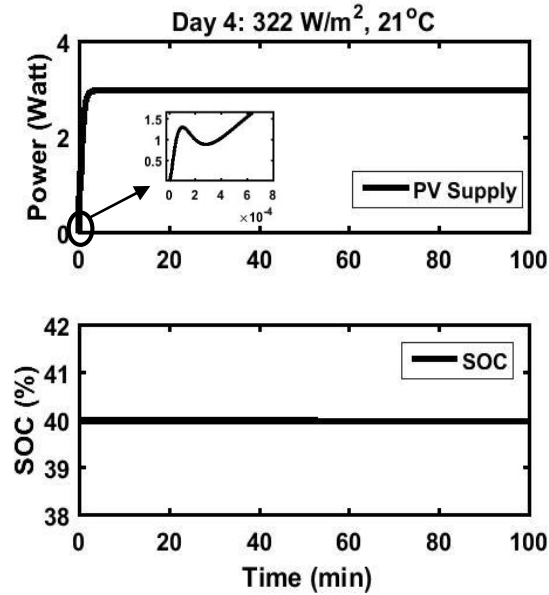


Figure 4.10: Experimental analysis for Day 4: 322 W/m^2 , 21°C

4.3.5 Modified AC Voltage

The research outcome is improved for DC supply voltage as well to expand the application facility. DC voltage generated from PV or battery was converted into 230 V , 50 Hz modified AC supply that is shown in Figure 4.11. The modified AC sine wave is generated in the laboratory condition. The modified AC sine wave limits from -230 V to $+230 \text{ V}$. It contains nearly 50 Hz frequency.

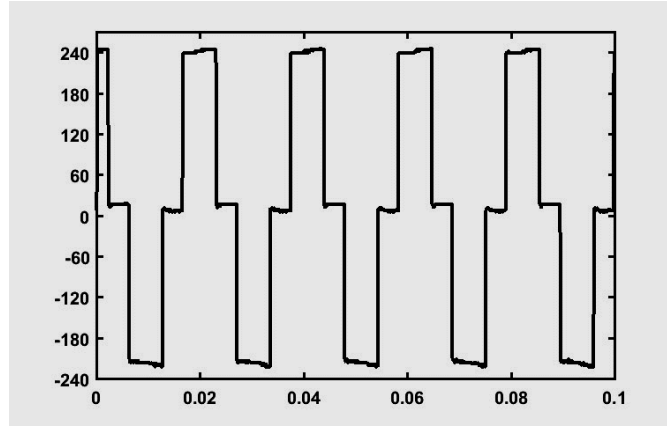


Figure 4.11: Modified AC Sine Wave by experimentation

4.4 Validation of the Robustness of the Proposed Methodology

The simulation and experimental examinations are performed in Section 3.2 and Section 3.3 respectively. In this section, the validation of the proposed work is given in relation to several possible factors such as SOC estimation, RMSE, Battery lifetime, modified AC sine wave etc. which are given onward.

4.4.1 SOC Estimation Accuracy

SOC estimation accuracy ensures the integral system efficiency of the battery storage section. The collected battery data was trained and tested via Matlab software which is shown in Figure 4.12. The regression for training, testing and validation is more than 90% as shown in Figure 4.13. Moreover, Figure 4.14 shows that though the initialization error for the proposed model is high owing to the random accessed weights of BPNN algorithm, the error is minimized as 0.082% after some moments as a result of weight adjustment tactics. Figure 4.15 indicates the RMSE of the estimated SOC. From the literature review, authors worked on the SOC estimation accuracy with different methodologies. However, the validation of the projected methodology is permitted through Table 4.1 that shows the comparison with other standing techniques.

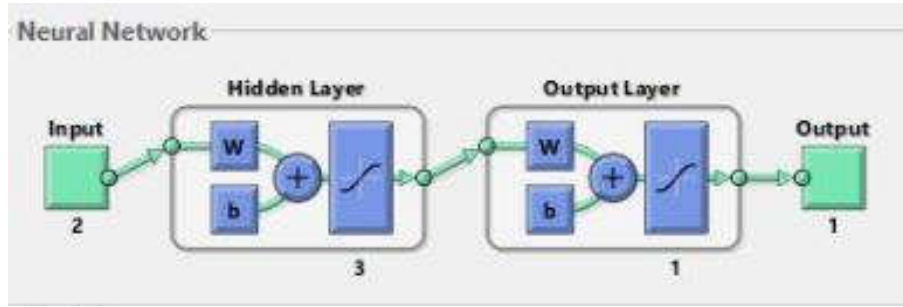


Figure 4.12: Neural Network modeling in Matlab software

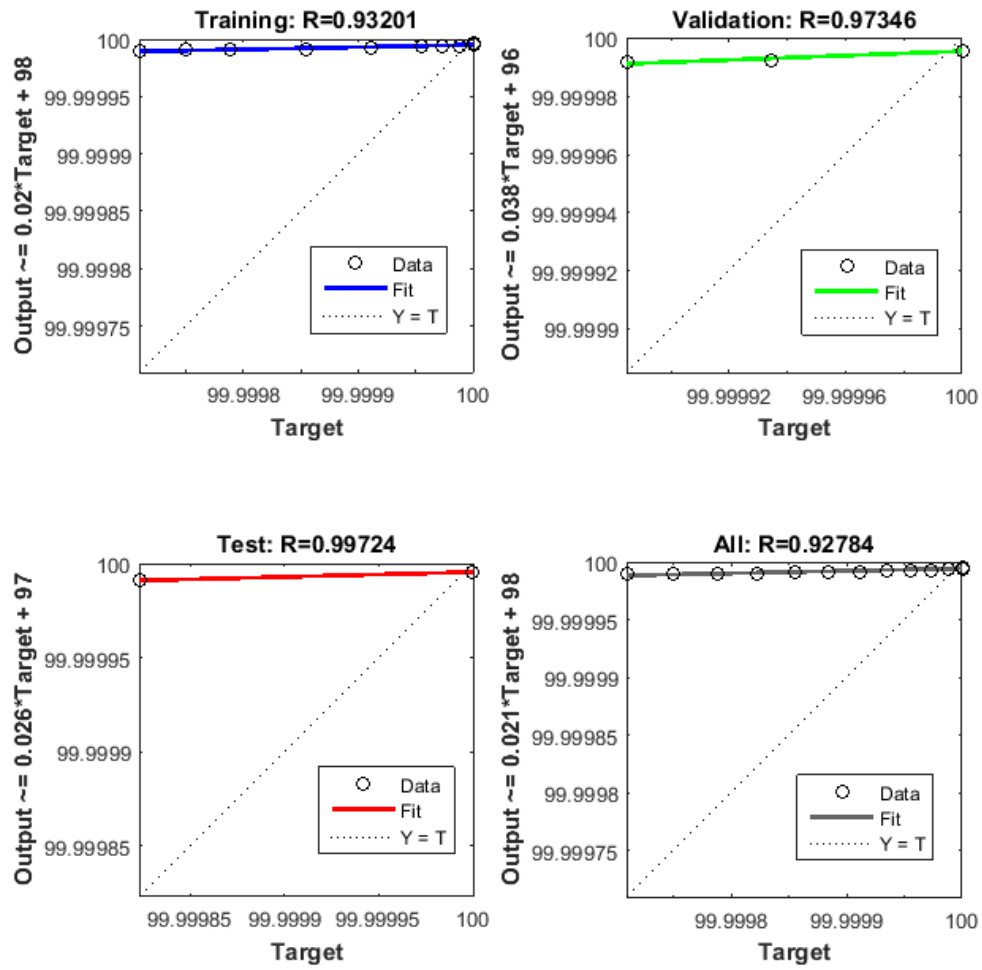


Figure 4.13: Training, Testing and Validation results with regression

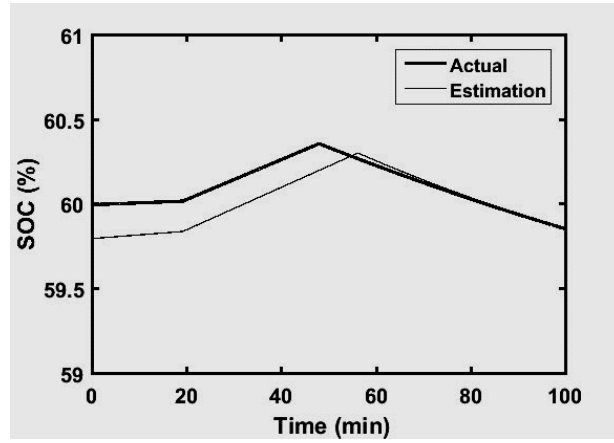


Figure 4.14: Comparison between Actual and Estimation SOC

Table 4.1: Comparison of SOC Estimation accuracy

Ref.	Year	Battery	SOC Algorithm	Error (%)
(Surendar V. et al., 2015)	2015	Lead Acid	SVR	0.95
(Morstyn et al., 2016)	2016	Lead Acid	KF	1.7
(Tran et al., 2017)	2017	Lead Acid	DEKF-ARX	4.58
(Azzollini et al., 2018)	2018	Lead Acid	PSO	3.46
(Al Hadi et al., 2019)	2019	Lead Acid	OCV	3.78
Proposed Model	2020	Lead Acid	BPNN	0.082

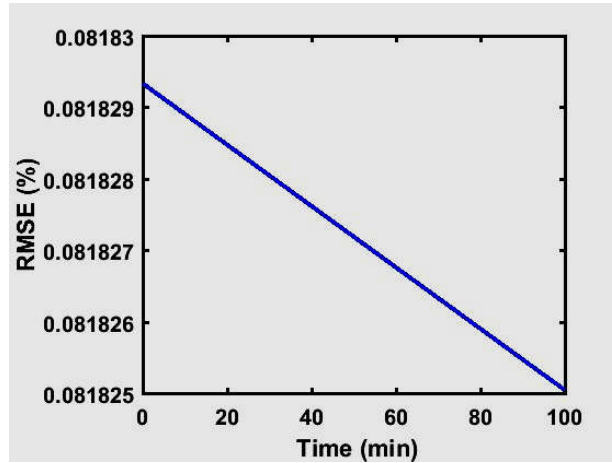


Figure 4.15: RMSE of the system

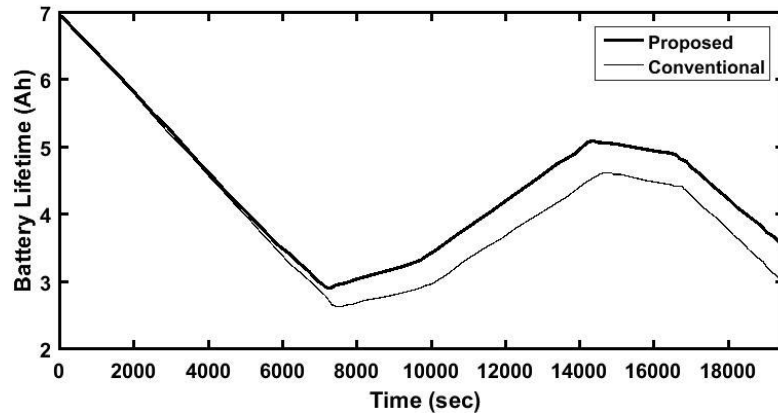


Figure 4.16: Battery Lifetime comparison between conventional and projected model

4.4.2 Battery Lifetime

The main principle for BMS is to lengthen the life of the battery. The projected model monitors the battery to maintain the SOC from 40% to 80%. Moreover, the control system makes a collaboration among the PV supply, load and battery. It implements PV supply and battery section as a main and secondary power supply respectively. It estimates battery SOC properly to prolong the lifetime of the battery. A comparison between the conventional and projected model of the Battery Lifetime is shown in Figure 4.16. From this

figure, it can be notified that the proposed model keeps 10% to 15% more Battery Lifetime compared to the conventional model.

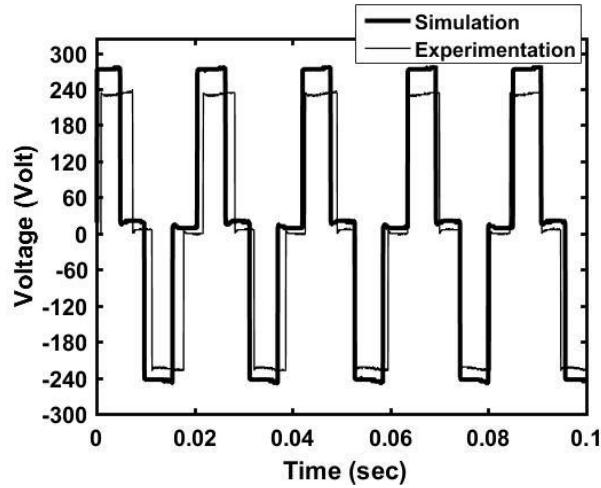


Figure 4.17: Comparison between simulation and experimentation Modified AC

4.4.3 Modified AC Sine Wave

To prove the robustness of the projected model, a comparison between simulated and experimented modified AC sine wave is shown in Figure 4.17. In both cases, nearly 230 V, 50 Hz modified AC voltage is produced. From the comparison of figure, it can be described that the simulation and experimentation is nearly same.

4.5 Summary

It is concluded that the simulation and experimentation analysis for BMS enhanced the battery lifetime successfully. Moreover, the accuracy of SOC estimation technique promoted the novelty of the current research. In every cases, the experimental validation followed the simulation work positively. The comparison of the present work with other standing methods, conveyed the robustness of the proposed work confidently.

CHAPTER 5

CONCLUSION AND RECOMMENDATION

5.1 Conclusion of the Study

Battery storage section is one of the most costly but dependable technique for PV-Battery integrated system. PV arrays cannot produce power during the night time as well as a small quantity is generated in the cloudy day. At this moment, battery power is the only supply command to support the load demand. A BMS of controlling outline is focused in this work that consists of PV model, P&O MPPT technique and BPNN based SOC estimation. Primarily, solar irradiance and atmospheric thermo data was collected from Renewable Energy Lab. The data was simulated via MATLAB 2019a for analyzing the real world application. Subsequently, the experimental evaluation of the simulated model is developed as well to prove the verification of the proposed model. dSPACE 1104 monitoring component upgrades the experimental qualification of the projected model. The principal objective of this research is to continue a nonviolent SOC window bound for the avoidance of over-charging or deep-discharging conditions. Effective simulation and experimentation for well-regulated BMS is followed to implement the Lead-Acid battery in the proposed structure to recover the best use of energy storage schemes combined with PV power system. The control strategy observes the SOC and takes decisions to arrive the anticipated operating goals by dint of broadening the battery life-time. The SOC estimation technique with RMSE 0.082% is compared with other existed methods. The control approach for PV-BMS validation tests conducted on this platform are innocuous beyond the standard range of operation, specifically at initial stages in the development procedure.

5.2 Proposals for Continuing Work

Generally, every single research is validated by following its detrimental deficiencies. Similarly, this research is conducted on account of uncompromising the aforementioned objectives in full-fledged. The projected model is perpetrated in the laboratory environment for sealed lead-acid battery by assuming the temperature as constant (25 °C). In this concern, the qualified data are perused alone that improved the battery lifetime around 10% compared to the conventional method. Moreover, the monetary outflows are extruded from this exploration which would play a cabalistic foreword in case of industrial application.

Consequently, the study suggests that future work should be performed to extend the development of the comprehensive algorithm at the request of protecting of battery storage section. The following recommendations are future work in the field of BMS.

- i. Different types of RESs and batteries are recommended to be carried out. The purpose is to investigate the storage system productivity prosecuting the economical aspects including the temperature involvement.
- ii. Further investigation for BMS is considered in case of utility or grid connected sectors in favour of analysing the storage portion efficiency.

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APPENDICES

Appendix A: Atmospheric data collection from Renewable Energy Lab, UNIMAS

DATE	Temperature (°C)	Humidity (%)	Solar Radiation (W/m ²)	Rain (mm)
5/29/2018	27.8	83.5	178.2	0.2
5/30/2018	27.9	84.8	148.3	10.2
5/31/2018	26.2	91.5	83.7	6.8
6/1/2018	25.9	90.3	95.4	29
6/2/2018	26.4	88.8	109.6	8
6/3/2018	27.3	86.1	82	0
6/4/2018	28.7	81.5	163.4	0.2
6/5/2018	28.3	84.6	151.9	1.6
6/6/2018	27.7	86.9	141.8	4.8
6/7/2018	28.7	83.6	152.3	0
6/8/2018	28.7	82.5	145.3	0
6/9/2018	27.7	84.7	119.8	0.2
6/10/2018	25.7	93.2	18.4	0
7/18/2018	31.4	65.8	215.8	0
7/19/2018	30.5	71.1	187.1	0.2
7/20/2018	29	76.3	182.5	27.4
7/21/2018	26.9	85.3	126.3	50
7/22/2018	27.1	84.8	118.3	0.2
7/23/2018	29.1	78.7	166.9	2.2

Appendix A continued

7/24/2018	29.6	77.3	179.9	0.2
7/25/2018	28.7	82.6	106.3	0.4
7/26/2018	28.4	82.4	129.5	0.4
7/27/2018	29.2	80.1	186.6	0.4
7/28/2018	27.4	88.9	61.1	5.6
7/29/2018	27	86.5	144.3	35.8
7/30/2018	27.2	86.4	162	0.2

Appendix B:

BPNN Code is mentioned below:

```
function [RMSE,SOC_Est] = fcn(V,I,SOC_Act)
i=0;
    V; I; SOC_Act;
% hidden neuron 3,
w1=.2;w2=.4;w3=.65;w4=.38;w5=.83;w6=.92;
w7=.28;w8=.52;w9=.76;w10=.18;w13=.34;w14=.54;w15=.93;
w11=.56;w12=.58; w16=.73; ita=.1;w17=.36;w18=.94;w19=.75;w20=.46;
for i=0:999
    i=i+1
    H1=w1.*V+w2.*I
    H1_act=1./(1+exp(-H1))
    H2=w4.*V+w5.*I
    H2_act=1./(1+exp(-H2))
    H3=w7.*V+w8.*I
    H3_act=1./(1+exp(-H3))
    SOC=w10.*H1_act+w11.*H2_act+w12.*H3_act
    SOC_Act
    SOC_Est=1./(1+exp(-SOC))
    RMSE=sqrt(mean((SOC_Act-SOC_Est).^2))
    if RMSE==0
        disp(RMSE)
    else
        % Backpropagation
```

```

% w10 w11 w12
del=(SOC_Act-SOC_Est).*SOC_Est.*(1-SOC_Est);
del_w10=del.* H1_act
w10=w10-ita.*del_w10
del_w11=del.* H2_act
w11=w11-ita.*del_w11
del_w12=del.* H3_act
w12=w12-ita.*del_w12
%Hidden Layer 1
del_hid1=(SOC_Act-SOC_Est).*SOC_Est.*(1-SOC_Est).*H1_act.*(1-H1_act);
del_w1=del_hid1.*V;
w1=w1-ita.*del_w1
del_w2=del_hid1.*I;
w2=w2-ita.*del_w2
% Hidden Layer 2
del_hid2=(SOC_Act-SOC_Est).*SOC_Est.*(1-SOC_Est).*H2_act.*(1-H2_act);
del_w4=del_hid2.*V;
w4=w4-ita.*del_w4
del_w5=del_hid2.*I;
w5=w5-ita.*del_w5
% Hidden Layer 3
del_hid3=(SOC_Act-SOC_Est).*SOC_Est.*(1-SOC_Est).*H3_act.*(1-H3_act);
del_w7=del_hid3.*V;
w7=w7-ita.*del_w7
del_w8=del_hid3.*I;
w8=w8-ita.*del_w8

end
end

%%% NNET Block Generation
clc;clear all;
p=csvread('Bat_Par');
vol=p(:,1);
cur=p(:,2);
net1=feedforward(3);
net2=trainngd(net1,vol,cur);
gensim(net2)

```

Appendix C:

PV Panel

The nominal ratings of SOLAR MODULE Solar Panel (Figure 1) is given below:

Maximum Power (+10%/-5%), ($P_{\max}$)	50.0 W
Open-Circuit Voltage, (V_{OC})	21.6 V
Short-Circuit Current, (I_{SC})	3.40 A
Voltage at Point of Maximum Power, (V_{mpp})	17.6 V
Current at Point of Maximum Power, (I_{mpp})	2.84 A
Application	DC 12 V

STC: Irradiance of 1000 W/m^2 , AM1.5 Spectrum and cell temperature of 25°C



Figure 1: PV Panel

Lead-Acid Battery

According to the SMNT MT12-7.0 from Figure 2 Sealed Rechargeable Battery, the nominal rating for the lead acid battery is given below:



Figure 2: Rechargeable Lead Acid Battery

Nominal Voltage	12 V
Nominal Capacity	7 Ah
Cycle use	14.4 V – 15.0 V
Standby use	13.5 V – 13.8 V
Initial Current	2.1 A

Load

DC Load (Figure 3)

Maximum Working Voltage	1000 V
Resistor Type: N	1214
PH	3
R	$3 \times 35 \text{ ohm}$
I	$3 \times 3.8 \text{ A}$
P	$3 \times 500 \text{ W}$

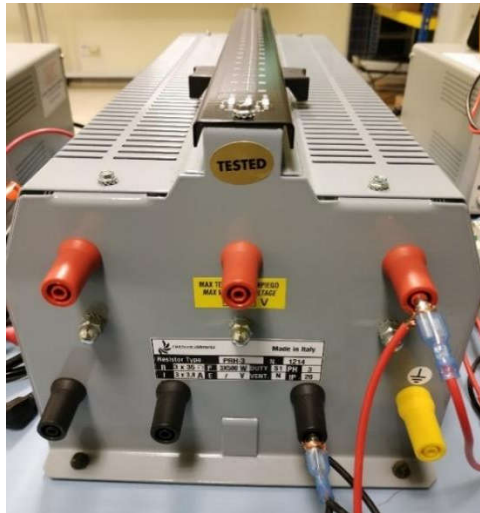


Figure 3: 3 phase Load

Inverter

Foshan Suoer Electronic Technical Parameters (Figure 4)

Waveform	Modified Sine Wave
Input Voltage	12 V (10.5 V – 14.5 V)
Built-in fuse	15 A / 20 A / 25 A
Low-Voltage Turn-off	9.7 – 10.3 V
Over-Voltage Turn-off	15 – 16 V
No Load Current	< 0.25 A
Efficiency	> 90 %
Continues Power	100 W / 150 W / 200 W
Surge Power	200 W / 300 W / 400 W

USB Output

DC 5 V 500 mA



Figure 4: Electronic Inverter



Figure 5: 5W LED Light

AC Light (Figure 5)

Brand name

Lorraine (ROLin)

product name

LED energy saving lamp

Product power

5 W

Rated voltage	220 V ~ 50 Hz
Product light color	White light 6500 K
physical dimension	φ40 * 110
Product light mouth	E27
Luminous flux	425 (Lm)
Color rendering index	> 75
The scope of application	Home / business / office



Figure 6: Voltage transducer

Sensors

Voltage Sensor (Figure 6) or LV25-P voltage transducer

Transducer Function:	Voltage Transformer
Supply Voltage Min:	-15 V
Supply Voltage Max:	+15 V
Accuracy %:	0.9 %

Operating Temperature Min:	0 °C
Operating Temperature Max:	70 °C
Input Current:	10 mA
External Depth:	29.2 mm
Output Current Max:	25 mA
Linearity:	0.2 %

Current Sensor (Figure 7)

LA25-NP Current Transducer

Part Number	LA 25-P
Description	SENSOR CURRENT HALL 25 A AC/DC
Voltage - Supply	±12 V ~ 15 V
Sensor Type	Hall Effect, Closed Loop
Polarization	Bidirectional
Packaging	Bulk
Package / Case	Module, Single Pass Through
Output	Ratiometric, Current
Operating Temperature	-25 °C ~ 85 °C
Mounting Type	Through Hole

Linearity	$\pm 0.15\%$
Frequency	DC ~ 200 kHz
For Measuring	AC/DC
Current - Supply (Max)	10 mA
Current - Sensing	25 A
Accuracy	$\pm 0.91\%$



Figure 7: Current Transducer

Relay Switch

Figure 8 shows the SONGLE Relay Switch that is used for this research. The feature of Srd 05Vdc SL-C is mentioned below:

Rated load	10 A, 250 VAC / 28 VDC, 10 A, 125 VAC / 28 VDC, 10 A 125 VAC / 28 VDC
Contact resistance	$\leq 100\text{ m}(\Omega)$

Electrical life	100,000
Coil rated voltage	3-48 VDC
Coil power	0.36 W, 0.45 W
Coil pick-up voltage	$\leq 75\%$
Coil drop-out voltage	$\geq 10\%$
Weight	10 g
Insulation resistance	≥ 100 Mohm
Ambient temperature	$-25 \sim 70$ °C

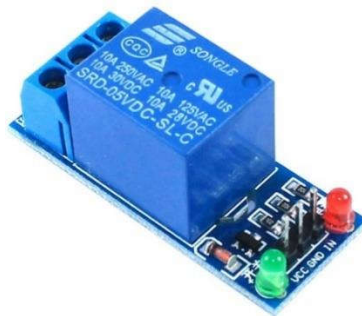


Figure 8: Relay Switch

Appendix D:

List of Publications

1. **Qays, O.**, Buswig, Y., Hossain, L., & Abu-Siada, A. (2020). Recent Progress and Future Trends on State of Charge Estimation Methods to Improve Battery-Storage Efficiency: A Review. *CSEE Journal of Power and Energy Systems*, 1(1), 1–17.
2. Buswig, Y., **Qays, O.**, Affam, A., Albalawi, H., Othman, A., K., Julai, N., & Yi, S. (2019). Designing a control system based on SOC estimation of BMS for PV-Solar system. In: Proceedings of IEEE, 2019 International UNIMAS STEM 12th Engineering Conference (EnCon). Kuching, Sarawak, Malaysia, 28 - 29 August 2019, IEEE Publisher.
3. **Qays, O.**, Buswig, Y., & Anyi, M. (2019). Active Cell Balancing Control Method for Series-Connected Lithium-Ion Battery. *International Journal of Innovative Technology and Exploring Engineering*, 8(9), 2424–2430.
4. **Qays, O.**, Buswig, Y., Hossain, L., & Abu-Siada, A. (2020). Active Cell Balancing Control Strategy for Parallel Connected LiFePO₄ Batteries. *CSEE Journal of Power and Energy Systems*, 2(3), 1–8.
5. **Qays, O.**, M., Buswig, Y., Hossain, M. L., & Abu-Siada, A. (2020). Active Charge Balancing Strategy Using the State of Charge Estimation Technique for a PV-Battery Hybrid System. *Energies*, 13(13), 1-8.