



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.

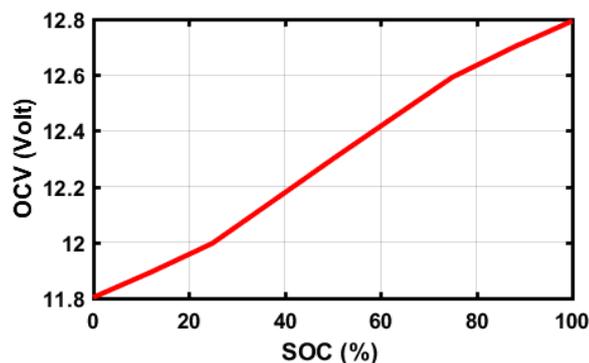


Figure 1.1: OCV vs SOC relationship for 12 V Lead-Acid battery status (Lee et al., 2017)

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.

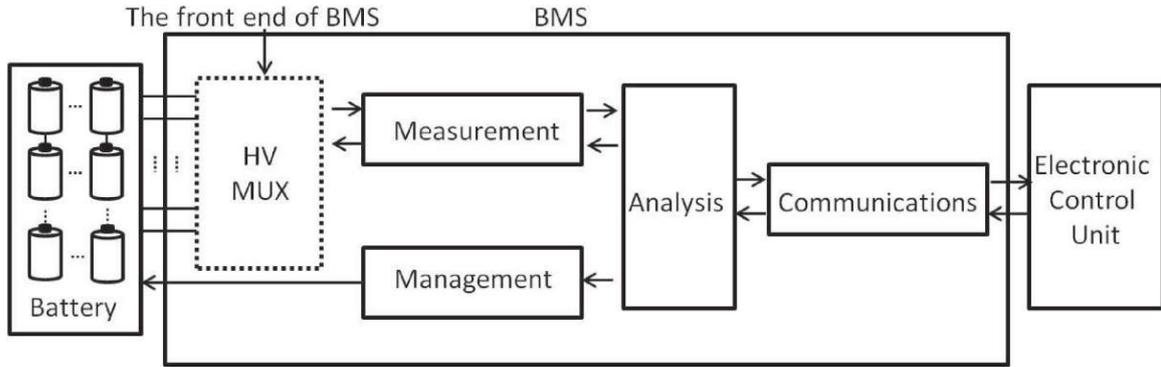


Figure 1.2: General model of BMS (Li et al., 2017)

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