DATA REDUNDANCY REDUCTION USING SENSITIVITY ANALYSIS METHOD FOR MACHINE-LEARNING-BASED BATTERY MANAGEMENT SYSTEM

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I hereby declare that the work in this thesis is my own except for quotations and summaries which have been duly acknowledged

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I dedicate this thesis report to my beloved parents, supervisors, sisters, family, and friends, thank you.

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ABSTRACT

This thesis proposes a sensitivity analysis method to reduce the computational effort of machine-learning (ML) techniques in the battery management system (BMS). The novel approach analyzes the sensitivity of lithium-ion battery model parameters towards their discharge performances. The sensitivity analysis is based on the sum-of-difference method to identify redundant model parameters that characterized the battery's discharge performance. From the sensitivity analysis, it is found out that the current, discharge time from state-of-charge (SOC), and power discharge output show minimum influence towards the variation of battery parameters. Thus, this finding indicates that current, discharge time, and power were redundant and may be excluded in the formation of the training dataset. The newly discovered finding is applied to the ML-based BMS. In the development of the training dataset, a reduced-sized dataset is formed by excluding current, discharge time, and power from the training dataset for the real-time battery-parameter monitoring in BMS. The newly formed reduced-sized dataset is applied to ML techniques: artificial neural network (ANN), deep learning (DL), and modified adaptive neuro-fuzzy inference system (MANFIS). Consequently, the training performances of all three ML techniques are observed, analyzed, and compared. The results demonstrate that the reduced-sized training dataset that is formed based on the sum-of-different method reduced the training time by up to 60.25% as compared with the full-sized dataset. Also, estimation accuracy is improved due to the improvement in training data bias. This result suggests that the proposed method significantly improved the training performance of the ML techniques in BMS application. The implementation of sensitivity analysis in the development of the training dataset for ML applications improved the performance of the real-time monitoring of lithium-ion battery parameters in advanced BMS applications.

ABSTRAK

Tesis ini mencadangkan kaedah analisis kepekaan untuk mengurangkan usaha komputasi teknik pembelajaran mesin (ML) dalam aplikasi sistem pengurusan bateri (BMS). Pendekatan baru ini akan menganalisis kepekaan parameter model bateri litium terhadap prestasi nyahcasnya. Analisis kepekaan ini berdasarkan kaedah jumlah perbezaan untuk mengenal pasti parameter model berlebihan mengikut ciri-ciri prestasi nyahcas bateri. Dari analisis kepekaan, didapati bahawa arus, tempoh masa nyahcas daripada keadaan nyahcas (SOC), dan kuasa keluaran menunjukkan pengaruh minimum terhadap variasi parameter bateri. Oleh itu, penemuan ini menunjukkan bahawa arus, masa nyahcas dan daya berlebihan akan dikecualikan dalam pembentukan set data latihan. Penemuan yang baru ditemui ini kemudian akan diterapkan pada BMS berasaskan ML. Dalam pengembangan set data latihan, set data ukuran lebih kecil dibentuk dengan mengasingkan data arus, masa nyahcas, dan kuasa daripada set data latihan untuk pemantauan parameter bateri masa nyata di BMS. Set data bersaiz kecil yang baru terbentuk digunakan untuk pelbagai jenis teknik ML: rangkaian saraf tiruan (ANN), pembelajaran mendalam (DL) dan sistem inferensi neuro-fuzzy adaptif yang diubah (MANFIS). Hasil menunjukkan bahawa kumpulan data latihan bersaiz kecil yang dibentuk berdasarkan kaedah jumlah perbezaan bagi mengurangkan masa latihan hingga 60.25% dibandingkan dengan set data ukuran penuh. Tambahan pula, ketepatan anggaran juga dapat ditingkatkan kerana peningkatan bias data latihan. Hasil ini menunjukkan kaedah yang dicadangkan meningkatkan prestasi latihan teknik ML dalam aplikasi BMS dengan sangat ketara. Pelaksanaan analisis kepekaan dalam pengembangan set data latihan untuk aplikasi ML meningkatkan prestasi pemantauan masa nyata parameter bateri litium-ion dalam aplikasi BMS termaju.

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LIST OF ABBREVIATIONS

AC	–	Alternating current
AI	–	Artificial intelligence
ANFIS	–	Adaptive neuro-fuzzy inference system
ANN	–	Artificial neuro network
ASMO	–	Adaptive spider monkey optimization
BMS	–	Battery management system
CCL	–	Constant current load
CIL	–	Constant impedance load
CNN	–	Convolutional neural network
CPL	–	Constant power load
DBN	–	Deep belief network
DC	–	Direct current
DL	–	Deep learning
ECM	–	Equivalent circuit model
EM	–	Electrochemical model
ESS	–	Energy storage system
FET	–	Field-effect transistor
GA	–	Generic algorithm
GSA	–	Global sensitivity analysis
HESS	–	Hybrid energy storage system
HEV	–	Hybrid electrical vehicle
IGBT	–	Insulated-gate bipolar transistor
IT	–	Internal resistance
K-NN	–	K-Nearest Neighbor
LCO	–	Lithium cobalt oxide
LED	–	Light emitting diode
LMO	–	Lithium manganese oxide

LTO	–	Lithium titanite oxide
MANFIS	–	Modified adaptive neuro-fuzzy inference system
ML	–	Machine-learning
MM	–	Mathematical model
MOSFET	–	Metal–oxide–semiconductor field-effect transistor
NB	–	Naïve Bayes
NCA	–	Lithium nickel cobalt aluminum oxide
NMC	–	Lithium nickel manganese cobalt oxide
NMPC	–	Nonlinear model predictive control
OCV	–	Open circuit voltage
PEM	–	Physic-based electrochemical model
PMS	–	Power management system
PSO	–	Particle swarm optimization
RE	–	Renewable energy
RNN	–	Recurrent neural network
SA	–	Sensitivity analysis
SMO	–	Spider monkey optimization
SOC	–	State of charge
SOH	–	State of health
SVM	–	Support vector machines

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CHAPTER 1

INTRODUCTION

1.1 Background of the study

Lithium-ion battery has a profound impact on modern industries and lies at the heart of many modern systems and devices. The battery continues to draw vast research attention as a promising energy storage system (ESS) technology due to its high energy density and high open-circuit voltage. ESS is a crucial technology in providing superior solutions in portable devices, transportation, and renewable technologies. Nevertheless, ESS is not merely a plug-and-play technology, as different system applications have different requirements in the power supply system.

Therefore, many types of research have been conducted to investigate the requirement of ESS for renewable energy farming, vehicle electrification, and residential application [1]–[4]. All these researchers provide different configurations, topologies, and control schemes to deliver the performance demanded by the applications. In addition, the researchers in [5], [6] pointed out that battery lifespan eventually degrades over time. A degraded battery is difficult to recycle and requires expensive equipment [7]. Consequently, this predicament reduces the ability of ESS to be fully developed due to the risk of low investment.

In the literature, a battery management system (BMS) is introduced to ensure that the lithium-ion battery delivers the required performance, whilst protecting and prolonging the lifespan of the battery. The controlling algorithms behind this technology extend from the simplest linear control to the application of machine-learning (ML) methods, such as artificial intelligence (AI) [8]–[11]. The basic linear controller is sufficient for a simple application, such as battery pack chargers, portable electronic devices, and renewable energy storage applications, while the machine-learning-based (ML-based) battery management system (BMS) provides an appropriate control for more complicated applications, such as electric vehicles, aerospace, and smart-grid power applications. Implementing an ML-based controller in the battery management system is known as an advanced battery management system. This control requires a comprehensive training dataset to provide the necessary control for the application.

1.2 Problem statement

An advanced BMS requires real-time information on the battery's state and internal parameters to impose safer constraints on the battery's operation. An ML application in advanced BMS estimates the real-time internal battery model parameters based on the battery's discharge output performance. However, the problem is the battery manufacturers only provide new battery parameter information for the typical BMS applications. This parameter information is not valid for real-time advanced BMS applications as the battery parameters are changing over time. Therefore, it is crucial to analyze the discharge performance of the battery measurements towards the variation of the battery model parameters under the degraded condition.

In order to represent the battery's dynamics, ML methods are trained using the input-output training dataset. The development of the training dataset is crucial in any ML-based application. Conventionally, ML works on the assumption that the training performance increases with the number of training data. This assumption is true to a certain degree. Hence, the application of ML tends to include all operating scenarios, which results in a huge training dataset. However, it is often found out that there is a lot of redundant data in the training dataset. These redundant data degrade the training performance of the ML application, especially on the training time. In the real-time battery model parameter estimations using the ML technique, the battery model is represented by a series of complex mathematical equations, characterized by various parameters to yield several output variables.

As a result, a huge training dataset is required to estimate the real-time battery model parameters accurately. As the battery degrades, these parameters change, and another set of a huge training dataset is required to represent this operating scenario. Thus, the size of the training dataset increases exponentially as the battery degrades over time. It has been found out that not all measurements are sensitive towards the variation in the parameters as the battery degrades. Therefore, a sensitivity analysis is required to identify the redundant measurements in order to reduce the size of the training dataset systematically. The reduction of the size of the training dataset will improve ML training performance in estimating the real-time lithium-ion battery model parameters.

1.3 Research objectives

This research aims to achieve the following objectives:

a) To analyze the discharge performance of the battery measurements towards the variation of the battery model parameters under degraded condition.

b) To determine the redundant measurement in the training dataset based on the sensitivity analysis using the sum-of-difference method of the battery model parameters.

c) To evaluate the performance of artificial ML techniques in the real-time battery model parameter identification application using the reduced training dataset.

1.4 Research scopes

This research is limited to the following scope:

a) The lithium-ion battery was modelled using the modified Shepherd's model. The battery simulation model was developed using the MATLAB Simulink software.

b) This research considered only lithium-ion battery as the case study. The ratings for the voltage and current of the battery are using 3.6V and 3.25A, respectively. A single cell of lithium-ion battery is considered because the investigation of battery degradation is normally conducted based on a single cell [12]. Battery degradation is normally different among the individual battery cell in real-time application. Different cell material resulted a different performance change. Hence, it is required to be tested in a single-cell condition for comprehensive investigation process.

c) The constant current load was considered to discharge the lithium-ion battery because most electrical loads draw a constant current in practice.

d) The battery discharge performance was simulated using the characteristics defined from the manufacturer's datasheet. Then, the characteristic of the battery model was varied under 500 cycles of degraded condition. The battery discharge performance was analyzed from the voltage, current, temperature, discharge time, power, and energy of the battery. ML techniques would be used to estimate the internal battery model parameters.

e) This study only considered the discharging process to simulate the discharge performance. This is because both processes of charging and discharging have similar performance characteristics [13]. The difference is only from the inverse discharge curve line produced.

f) This research considered artificial neural network (ANN), deep learning (DL) and modified adaptive neuro-fuzzy inference system (MANFIS) as the ML techniques to estimate the internal battery parameters. These techniques are considered because the configuration is less complex, while the estimation accuracy is at a satisfactory level.

1.5 Thesis organization

This thesis is organized into five chapters. Following this introductory chapter, the remaining chapters are described briefly as follows:

Chapter 2 presents the related background of the ESS technology. The current status, prospect, possible challenges and solutions are briefly discussed in this chapter. Moreover, this chapter also discusses the sensitivity analysis approach for data-driven applications. The various purposes of this approach are concisely discussed in this chapter.

Chapter 3 presents in-depth the proposed research methodology used in this work to reach the objectives. The battery modelling, sensitivity analysis process, and machine-learning implementations are elaborated thoroughly in this chapter. Also, the flowchart diagram of the methodology is presented in this chapter.

Chapter 4 discusses the results and the performance of the proposed methodology in terms of accuracy and computation time. Moreover, the performances of the proposed method using various machine-learning algorithms were compared to show the superiority of the technique.

Chapter 5 summarizes the main contributions and limitations of this study and provides some future insights from this research.

CHAPTER 2

LITERATURE REVIEW

2.1 Overview

This chapter highlights the importance of the work presented in this thesis. In this chapter, a review of the ESS technology cements the foundation of this research. Then, the battery technology used in practice is discussed to stress the need for the BMS. Next, the evolution of the BMS is reviewed. The need for an advanced BMS is also discussed in this chapter. Afterwards, the sensitivity analysis methods available in the literature to identify the redundant data are reviewed. Finally, the research gap, which founded the base of this research, is summarized.

2.2 A review on future ESS technology

In the literature, several works have reported on the latest ESS technology development in various applications and with different focuses. In [14], the researchers discussed the present status of lithium-ion battery technology. The discussion focused on the electrochemical aspect and the potential materials to improve the energy storage capability and the power output of lithium-ion batteries.

Meanwhile, the studies in [15] and [16] reported the technology development of the energy storage system for applications in transportation and main power grid. The studies focused on power converters and power storage technologies for various applications. The researchers in [17] discussed the ESS architectures utilized in practice, focusing on the development of control algorithms that optimize ESS utilization. Next, the maturity of storage energy technologies to facilitate the load demand for daily energy consumption was reviewed in [18]. On the other hand, the researchers in [19] reviewed the energy storage technology for hybrid electric vehicle (HEV) application. The report focused on the evaluation of the technology readiness of distinct components of the vehicle, especially on the electrical propulsion system. Figure 2.1 shows a typical block diagram of the energy storage system for electric vehicle application.

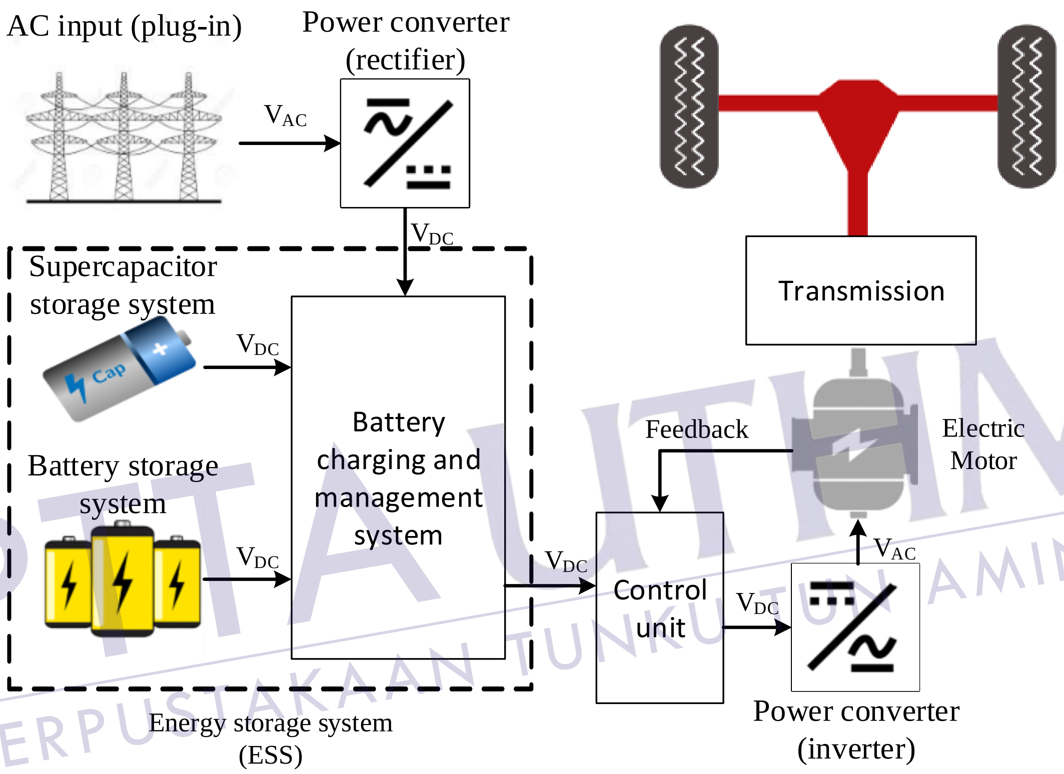

Figure 2.1: Block diagram of the energy storage system for electric vehicle application

From the aforementioned applications, the energy storage technology has a tremendous impact on electrical utility development, especially in renewable energy (RE) integration with the conventional power network. Figure 2.2 shows a typical block diagram of the residential RE system integration with the electrical grid system. The system consists of several sub-systems that are vital to ensure the continuity of electricity supply to residential customers [20]. It is well noted that RE is not always available to customers due to its intermittency nature. Thus, the RE resources are regulated to charge the ESS when the energy is available. Thus, the

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