AN ADVANCED MACHINE LEARNING APPROACH TO ESTIMATE THE STATE OF CHARGE OF BATTERY ENERGY STORAGE SYSTEM FOR MICRO-GRID

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Degree of Master of Science

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DECLARATION

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Name of the supervisor 1: Prof.K.T.M.U. Hemapala

Signature of the supervisor 1: Date

Name of the supervisor 2: Prof.J.P. Karunadasa

Signature of the supervisor 2: Date

ABSTRACT

Microgrids and energy storage systems play a major role in the sustainable and clean energy sector. There are various types of energy storage systems (ESS) are available and among them, battery energy storage systems (BESS) are the most effective technology due to their high reliability, availability of different scales, less environmental impact, dynamic local voltage support, etc. Whereas it has been seen that few drawbacks when it is in operation such as load dynamics caused by renewable energy fluctuation, battery state of charge level variation, extreme heat buildup, temperature effect for the battery performance and loading imbalance, single phase generating systems, short term loading by electric vehicle charges. Therefore, to investigate such kinds of issues, battery modeling is required. This study mainly focused on battery modeling. For that, first, developed an accurate battery model based on the electrical and thermal behavior of the battery. Battery parametrization is an essential part of battery modeling to investigate the conditions of the battery under different temperatures and charge/discharge rates.

In the proposed battery model, a second-order equivalent circuit model is used to identify the electrical parameters. It is the most preferred model because it accounts for the dynamics of charging or discharging currents than other available models. The thermal model is also investigated in detail by using heat generation inside the battery due to electrical loss and entropic heat. The three experiments performed on the battery cells to identify the battery parameters are constant current-constant voltage charge, constant current discharge, and pulse discharge. In each experiment, battery voltage, battery current, state of charge, battery capacity, surface temperature, and core temperature variations are analyzed and recorded while the ambient temperature is kept constant using a thermal chamber. Finally, model parameters are validated with the theoretical results. In addition to the above study, an accurate battery SOC level estimation method is developed via deep learning architectures, and the battery core temperature estimation model is developed by only using measurable parameters of the battery. Those studies can improve the accuracy of the battery parametrization procedure.

Keywords— Battery management system, State of charge, Electrothermal battery model, Parameterization, Validation, Heat generation. Deep learning, Time series forecasting, Python, Prediction, Kalman filter.

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BESS	:Battery Energy Storage System
BMS	:Battery Management System
OCV	:Open Circuit Voltage
SOC	:State of Charge
EV	:Electric Vehicles
ECM	:Equivalent Circuit Model
DNN	:Deep Nueral Network
RNN	:Recurrent Nueral Network
CNN	:Convolutional Neural Network
DBN	:Deep Belief Network
DRL	:Deep Reinforcement Learning
NN	:Neural Network
BP	:Back Propagation
MLP	:Multilayer Perceptrons
SGD	:Stochastic Gradient Descent
NARX	:Nonlinear Autoregressive Network
LSTM	:Long Short Term Memory
AR	:Auto-Regressive
MA	:Moving Average
ARIMA	:Auto-Regressive Integrated Moving Average
PI	:Performance Indices
CT	:Computational Time
MSE	:Mean Squared Error
MAE	:Mean Absolute Error
UKF	:Unscented Kalman Filter
EKF	: Extended Kalman Filter