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MODELLING LI-ION BATTERIES WITH DISTINCT CHEMISTRIES USING NOVEL AND ADVANCED SYSTEM IDENTIFICATION-BASED DATA DRIVEN APPROACH

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Abstract
The quests for reliable and efficient energy storage solutions have resulted in the evolution of modern Li-ion batteries. Recently, they have emerged as strong contender amongst all the storage battery types for reliable and efficient energy storage in the form of charge. Li-ion technologies have prevailed over others on account of their high energy density and specific power besides excellent charge-discharge cycles and low self-discharge rates. Performance of the batteries is generally regulated using battery management systems (BMS). It performs the real-time measurement of battery parameters such as current, voltage, power and temperature. It also predicts the values of these parameters through the incorporated battery models. The measured and predicted set of values are compared to estimate the battery state of charge (SOC), state of health (SOH) for performing optimal thermal and energy management during charging and discharging. Precise battery models are therefore essential for accurately estimating the states and optimizing the energy and thermal management strategies. Hence, accurate battery model is an essential factor for the development of BMS control algorithm. Equivalent circuit models (ECM) being now-a days widely incorporated within BMS contain a voltage source, a series resistance and one or two resistance-capacitance pairs connected in parallel. ECMs are simple and fairly accurate enough to model the thermo-electric behavior of a battery, but are manifested with certain inherent inaccuracies failing to imitate the electro-thermochemical battery behavior. This paper intends to use modern and advanced data driven method called system identification approach to generate batter and accurate models of three different chemistries (NCA, NMC, and LFP) of Li-ion battery.
For each of the chemistries; a *linear transfer function model* and a non-linear *Hamm-Wiener model* has been realized using *system identification* technique. The mathematical metrics of the degree of fitness between the reference and simulated models were used to choose the optimal and best model. In comparison to the linear model the non-linear model was obtained to be more accurate for all the batteries chemistries. The accuracies achieved by the non-linear Hammerstein-Wiener models for NCA, NMC, and LFP are 94.15%, 92.23%, and 90.78% respectively.

Index Terms- System identification, Hammerstein-Wiener model, Lithium-ion battery, Nickel-Cobalt-Aluminum Oxide (NCA), Nickel Manganese Cobalt (NMC) and Lithium Iron Phosphate (LFP).

1.INTRODUCTION

Li-ion batteries have replaced their counterparts in almost every application including electric-vehicles and renewable energy storages in the recent past. Their widespread use is the result of advantages in the form of properties such as higher energy density and power density at a modest increase in the cost [1]. The need for better battery performance in different applications has risen with the introduction of Li-ion batteries. It takes a good, dependable, and effective battery management solution to boost battery performance. Battery monitoring, estimation, and protection are the responsibilities of battery management systems (BMS). Precise battery models are required for efficient BMS design and simulation. Accurate battery modelling helps in real-time battery behaviour prediction [2], [3]. Moreover, for accessing the battery performance and measurements, they should be tested in various conditions. Setting up real time experimental set-ups are most of the times costly and unaffordable during testing and prototype development stage. Several models such as mathematical, electro-chemical and equivalent circuit models (ECM) have been demonstrated by the researches in the past

to represent the static and dynamic behaviors of battery. ECMs are the most widely utilized battery models capable of mimicking both the static and dynamic battery characteristics. In these models a combination of series and parallel resistances are used to represent the battery behavior [4]. A dc voltage source that fluctuates nonlinearly with the battery's state of charge serves as the open-circuit circuit voltage (OCV) of the battery as depicted in figure 1.

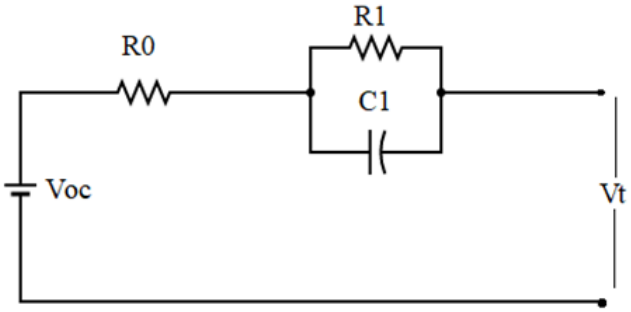

Figure 1: Equivalent circuit model [5].

The mathematical models lack accuracy due to poor correlation between model parameters and batter I-V properties thereby rendering them unsuitable for adoption in various applications. The ECMs such as 1-RC model requires lot of tests in order to capture the behavioral signatures of the battery. The 2 RC model and 1 RC with hysteresis model has a very high computing cost and are largely complex. Hence, dynamic applications that require speedy processing shouldn't use the 1RC with hysteresis mode [6], [7]. Therefore, new models involving both the traits such as accuracy and less computational speeds must be adopted involving novel data driven techniques [8].

In this paper, the efficacy of system identification technique for creating different models of Li-ion battery is tested. Linear transfer function models as well as non-linear Hammerstein wiener models for three chemistries of Li-ion batteries are estimated and the accuracies of each estimated model is tested by using the input-output data. The three different chemistries namely, Nickel Cobalt Aluminum (NCA) Oxide, Lithium Nickel Manganese ((NMC) oxide, and Lithium Iron Phosphate (LFP) are taken for estimation and performance evaluation. For each of the chemistries the linear transfer function model and non-linear Hammerstein-Wiener models are estimated using system identification technique. The performance these models in terms of accuracies are evaluated and compared for the each of the above mentioned chemistries and the results are analyzed so as to determine the models with highest accuracy.

This paper is structured as follows:
Introduction in section 1 is followed by literature review on the various mathematical modelling approaches followed for Li-ion and other battery types in section 2. Section 3 contains the overview of system identification approach for mathematical modelling and also the steps involved in modelling using system-identification technique. The various linear and non-linear models created for the three chemistries (NCA, NMC, and LFP) of Li-ion batteries are presented in section 4. Finally, the conclusions inferred are presented in section 5.

2. Literature Survey

A thorough assessment of the battery modeling literature is presented in this section. To determine the scope of the research, a comprehensive overview of the modeling methods used for Li-ion batteries adopted by various researchers in the past have been listed along with their brief illustrations.
Johnson (2002) summarized the battery modeling capabilities of ADVISOR, a MATLAB/Simulink-based advanced vehicle simulator developed by the National Renewable Energy Laboratory (NREL). They provided the battery models' equations or ECMs and demonstrated the models' accuracy using information obtained from battery testing that mimic real driving cycles. The used models were: (a)

an internal resistance model, (b) a RC model, (c) a PNGV capacitance model, and (d) ANN based lead-acid battery model. By employing a power as an input, the ADVISOR models were integrated with the vehicle system which forecasted current, voltage, SOC, and temperature of the battery.

Liaw *et. al.* (2007) addressed the equivalent-circuit models (ECM) for forecasting their battery cycle and calendar life by modeling battery performance, in terms of capacity change with cycling and ageing circumstances. They then used experimental validation to confirm the models' predictions and helped in determining a reliable battery life estimate.

Dubarry *et. al.* (2008) demonstrated an analogous circuit technique for simulating battery performance from a single cell to battery pack. When intrinsic imbalance among the cells was taken into account, the authors concluded that the SOC dependence of polarization resistance in individual cells was critical for improving prediction at the pack level. In their study the authors observed that correct resistance mapping was necessary for obtaining an accurate match in characteristics such as SOC and age, as well as improving battery simulation at the cell and pack levels. They also focused on constructing sophisticated battery models without detailed chemical expertise; using an integrated testing and simulation technique (ITS).

Rahmoun *et. al.* (2012), on the basis of two separate equivalent circuit diagrams and an extended Kalman filter, provided the principles for a new method of determining the state of charge (SOC) of Li-ion batteries (EKF). It explained how to use typical measurements to determine the parameters of these circuits. The findings of the measurement and computation were found to be in good agreement. The dependence of these factors on temperature and battery age was ignored in the first phase.

Thanagasundram *et. al.* (2012) proposed a second-order equivalent circuit for a lithium battery their research work. Hybrid power pulse characterization (HPPC) test was used to identify the battery parameters. The model parameters were identified using MATLAB software. The voltage error between the model's estimated voltage and real cell measurements was calculated using a validation method. For a 10%-90% SOC, the modelling error was 3%. The ohmic resistance values acquired in the parameter identification approach was verified using the current pulse technique. This technique also explored the effects of cell chemistry on the proposed models.

He *et. al.* (2012) summarized the seven representative battery models, which were either equivalent circuit models or simplified electrochemical models. After the model equations were constructed, the model parameters were identified using an online parameter identification. This was done on an experimental bench and the experiments were performed on schedule to evaluate the seven battery models in order to precisely predict the terminal voltages. The number of parallel RC branches was also taken into account. The results showed that the Double Polarization model, which is an equivalent circuit containing two RC networks, exhibited the best performance.

Yuan *et. al*. (2013) proposed the ARX model to mimic the nonlinear dynamics of the battery. This study explained the order selection theory and parameter identification method in depth. The HPPC cycles were used to identify and validate the model on a 60AH, LiFePO4 battery module. The extended Kalman filter was used to estimate SOC based on the suggested ARX model. The battery models' flexibility and the robustness for the SOC estimation algorithm was also tested. The results suggested that the SOC estimate approach employing the Kalman filter based on the ARX model exhibited outstanding performance. It boosted the model output voltage accuracy, thereby having the potential to be employed in EVs and HEVs.

Yao et. al. (2013) developed an electrical battery model for lithium ferro phosphate battery in MATLAB/Simulink. The developed battery model was validated from the experiment results. From the comparison, it was revealed that the developed model was capable of predicting current-voltage performance accurately.

Gao *et. al.* (2015) presented the modelling of a 50 Ah Li-ion battery utilized in a smart battery power system. The model was evaluated at various SOC levels. It was also experimentally verified that the obtained cell model was capable of simulating the battery behavior accurately in a specified range.

Zhang *et. al.* (2017) created an electrical battery model for lithium ferro phosphate batteries. Experimental findings were used to validate the created battery models. Based on the comparison, the constructed model was found to be capable of properly forecasting the current-voltage performance.

Madani *et. al.* (2019) evaluated a second-order equivalent electrical circuit battery model for a 13 Ah lithium titanate oxide battery cell. For the parameterization of the model, the pulse charge and discharge were used. At various SOC levels the temperature, load currents, and the battery cell's internal resistance, open-circuit voltage, and its capacity were measured. The results of the simulation were compared with the measurements taken in the lab. The proposed lithium-ion battery model was proven to be accurate. The proposed model was evaluated, and it was found to be able of predicting the current and voltage performance with great accuracy.

Nemes *et. al.* (2019) presented the Li-ion cell's first-order RC equivalent circuit model (ECM). Experimental observations on a genuine Li-ion cell were used to identify the model parameters. After measuring the discharge capacity, the open-circuit voltage (OCV) and parameters for the equivalent circuit components were determined using continuous current pulses after the cell had been fully charged and discharged. The circuit parameters for one ECM were generated using single discharge pulse administered at around 60% SOC, while the circuit parameters for the second model were calculated for each discharge pulse and saved in a look-up table based on the SOC examined.

Alsabari *et. al.* (2020) examined the second-order model for characterization of lithium-ion batteries. For this a KCL model was created in MATLAB. A battery tester gadget was used to determine the internal specifications of the battery. Initially, the coulomb counting method was used to estimate the SOC. Using experimental terminal voltage data and SOC along with a lookup table, the initial SOC estimation was performed. The simulated terminal voltage as well as the battery's state of charge (SOC) were compared with measured data and validated. For terminal voltage and SOC, respectively, the highest relative error was 0.015V and 2%.

Tran *et. al.* (2021) evaluated the performance of three distinct ECMs (1RC, 2RC, and 1RC with hysteresis) on four Li-ion battery chemistries (LFP, NMC, LMO, and NCA). The findings showed that all three models were accurate enough to be used for the four different Li-ion chemistries. In comparison to non-dynamic current profiles, ECMs performed better in dynamic current profiles. The 1RC with hysteresis ECM performed best between LFP and NCA, whereas the 1RC ECM performed best for NMC and LMO. Various ECMs were found to be suitable for various Li-ion battery chemistries in this investigation.

Tamilselvi *et. al.* (2021) conducted a thorough examination of numerous battery models for various batteries types, including electrochemical models, mathematical models, circuit-oriented models, and combination models. They also explored the benefits and limitations of certain modelling techniques. The application of numerous machine learning and meta-heuristic methods for BMS described. They used black box and grey box methodologies to model the Li-ion batteries charging and discharging properties. The methodologies, benefits, and drawbacks of black box and grey box battery modelling were investigated. In addition, using evolutionary algorithms, a study was conducted to extract the parameters from a lithium-ion battery model.

Guo *et. al.* (2022) provided a summary of the advancements in ECM-based online state of power (SOP) estimate approaches during the last decade. Here, online SOP estimate approaches were briefly discussed in terms of various operation modes, as well as their key benefits and drawbacks. Secondly, three elements such as battery modelling, online parameter identification, and SOP estimation were evaluated. Finally, the accuracy and effectiveness of several SOP testing methodologies were discussed.

Kayastha *et. al.* (2022) focused on identifying the various battery parameters associated with EV batteries and developing a simulation model that could provide an initial idea to the designer regarding battery pack design and assist in selecting the type of battery with limited space.

All the above studies performed by the academicians highlighted the importance and need of data driven accurate battery models often required for incorporation within the BMS for better operation of EVs.

3.Materials and methods

In this section a brief overview of the approach adopted for creating the battery models is discussed. The system identification approach for modelling of systems have been briefly highlighted and the types of models that can be created using the system identification approach is also discussed.

System identification technique

Interrelation among the different variables of a system is required in order to understand its behavioral dynamics. Interactions between the system's variables are described by mathematical models, which are useful for modelling and prediction of the system behavior. System identification is a method for building mathematical models of dynamic systems by measuring the input and output signals of the system [9], [10]. It provides tools for creating mathematical models of dynamic systems utilizing input/output data that has been observed. In order to build a system model using system identification approach, the input and output signals are monitored, collected, and subjected to data evaluation [11], [12]. The identification approach, facilitates the development and application of models for such dynamic systems that are hard to model using precise specifications or valid logic [13], [14].

Model structures

Several models for a physical system can be realized using system identification technique. Broadly these model structures are classified as linear model structures and non-linear model structures. A brief description of the linear and non-linear model structures are presented in the sections below.

Linear model structures

Using system identification approach mainly three linear model structures can be realized. These model structures are transfer function model, state-space model and Grey-box model [15]. The transfer function represents the system as ratio of two polynomials for the system representing its input and output in terms of Laplace operator; considering the initial conditions for the system as zero as given by (i).

$$T(s)= Y(s)/U(s) \quad (1)$$

While forming the state space model for a system, the state variables representing the system are identified and the inter-relation between these variables are represented in the form of 1st order differential equations represented by (ii).

$$x = A\dot{x} + Bu \quad (2)$$

Where x is the state vector, u is the input to the system, A is the nxn state matrix, B is nx1 input matrix. The Grey box model for a system can be identified

Non-linear model structures

The actual physical systems contains different types of non-linearities. In the cases where the system is operated in linear region these non-linearities can be removed from the models and only linear models can be considered for their accurate analysis [16]. However, for the input conditions when the linear models become insufficient to accurately represent the system dynamics, the non-linear models can be used for more accurate analysis [17]. The relationship between the input and output of a dynamic system in discrete time is given by equation (3).

$$y(t) = f(u(t - 1), y(t - 1), u(t - 2), y(t - 2), \ldots) \quad (3)$$

where y(t) represents the output vector and u(t) represents the input vector for the system.

The system is non-linear if the function f is non-linear, representing the arbitrary non-linearities present in the system such as switches, saturations and dead-zones etc. System identification approach facilitates the modelling of non-linear physical systems in three forms as represented in figure 2.

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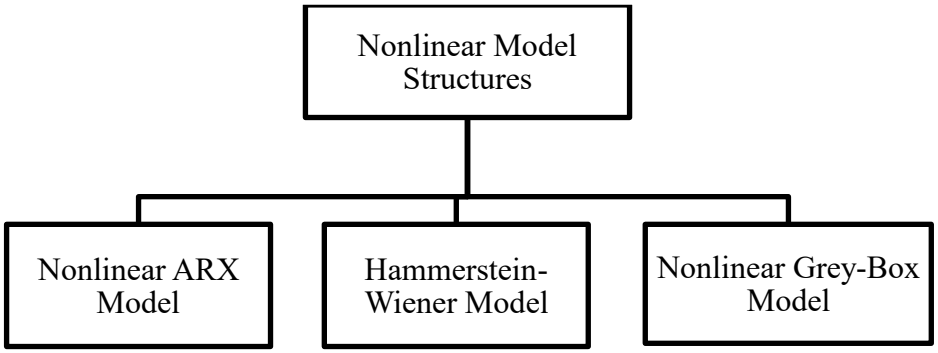

Figure 2: Non-linear model structures

Non-linear ARX model

Non-linear ARX model is the extension of linear ARX model and have the general structure represented by equation (4)

$$y(t) = f(y(t - 1), ..., y(t - nc), u(t - nk), ..., u(t - np - nd + 1)) \quad (4)$$

where the function f depends on the values of finite previous inputs u and outputs y. nc represents the number of past output terms and nd represents the number of past input terms necessary for predicting the current output. np is the delay between input and output represented in terms of number of samples. The ARX model structure facilitates modelling complex non-linear system with the help of flexible wavelet and sigmoid non-linear functions representing the non-linear component of ARX model.

Hammerstein-Wiener model

In Hammerstein-wiener model; one or two static non-linear blocks are connected in series with a linear block representing the system dynamics in the form of a discrete transfer function as depicted in figure 3.

Where, w(t) = f(u(t)) is a non-linear function transforming input data u(t) and w(t) has the same dimension as u(t) and x(t) = (b/f)w(t) is a linear transfer function and x(t) has the same dimension as y(t).

The linear block is a transfer function matrix represented by equation (5).

$$\frac{b_{i,j}(q)}{f_{i,j}(q)} \quad (5)$$

where, i = 1, 2,…… ny and j = 1,2,...,nu

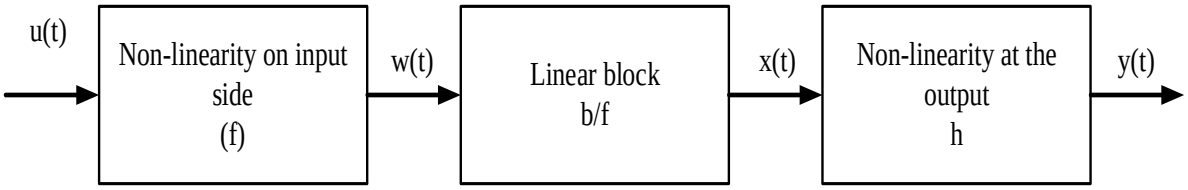

Figure 3 Block diagram of Hammerstein-Wiener model [18].

This model suitably fits into black-box form for physical systems without representing their exact dynamics or for modelling those systems containing non-linearities such as dead-zones and saturation [16], [18]. These models can be used to model complex chemical processes where it becomes difficult to identify each and every factor involved in a chemical phenomenon.

Methodology

In this section, the methodology adopted for modelling the Li-ion batteries of three different chemistries such as NCA, LFP and NMC has been discussed.

System Identification methodology

A model structure is a mathematical relationship with unknown parameters between input and output variables. In order to estimate the values of movable parameters in a particular model structure, system identification uses the input and output signals measured from a system. We can create models employing frequency response data, time-series signals, time-series spectra, and time-domain input-output signals. One need measured data that accurately captures the dynamic behaviour of the system

in order to create a good model of it. A simple model structure is given by the difference equation represented by equation (6).

$$y(k) + ay(k-1) = b\,u(k) \quad (6)$$

Where, 'a' and 'b' are adjustable parameters. The system modelling using system identification process involves four basic steps as depicted in the flow chart of figure 4.

- *Data collection:* A data set gathered from a test that was specifically created to reveal important system behaviour. It is cleaned up by removing outliers and trends, and only the most important bits of the raw data are kept. Filtering could be used to improve significant frequency ranges.
- *Best model choice:* Model estimation and selection of identification method: Determine the optimal model inside the model structure based on the input - output data and a predetermined fit criterion. A technique for identifying objects that attempts to alter the internal model parameters to suit the model's simulated results to the observed data set.
- *Model parameter estimation:* Determine the optimal model inside the model structure based on the input - output data and a predetermined fit criterion. A technique for identifying objects that attempts to alter the internal model parameters to suit the model's simulated results to the observed data set.
- *Model validation and comparison:* Examine the attributes of the resulting model. If the model is sufficient, stop; if not, try a different model set and try other estimation techniques and continue working with the input - output data.

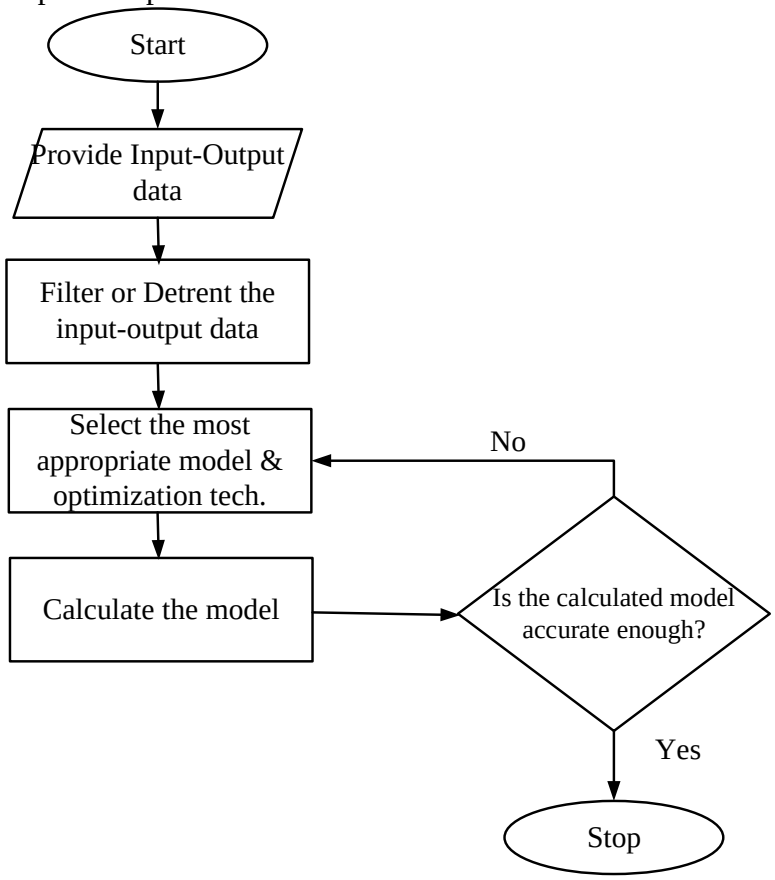

Figure 4: System identification work-flow process.

Data collection approach from batteries

The specifications of Li-ion batteries used for modelling is given in table 1. The input output data from each of the battery types was collected by performing hybrid pulse power characterisation (*HPPC*) test through simulation. The *HPPC* test is a frequently employed test involving applying charging

discharging pulse of certain duration into the battery and measuring its current change. This test is primarily carried out to assess the battery's ability to provide voltage levels while it is operating under different loading conditions. Its major goal is to establish the maximal and minimal battery voltage levels after charge and discharge pulses, respectively. The HPPC test is capable of taking the voltage and current signatures of the battery during charging and discharging process, thereby helping in accurate battery modelling.

Each of these battery types were put through a five-pulse discharge HPPC test (0.5C, 1C, 2C, 4C & 6C) at 100%-0% SOC.

Figures 5-7 represent the time-plot of the input current and the output terminal voltage (no load) of each battery determined by the HPPC test. These curves show the terminal voltage and currents of the batteries at each discharge and charge pulse.

Li-ion battery type	Manufacturer	Name	Nominal Capacity (Ah)
NCA	Panasonic	18650PF	2.9
NMC	Samsung	INR21700-30TSN001	3.0
LFP	A123 SYSTEM	ANR26650M1-B	2.5

Table 1: Battery specifications.

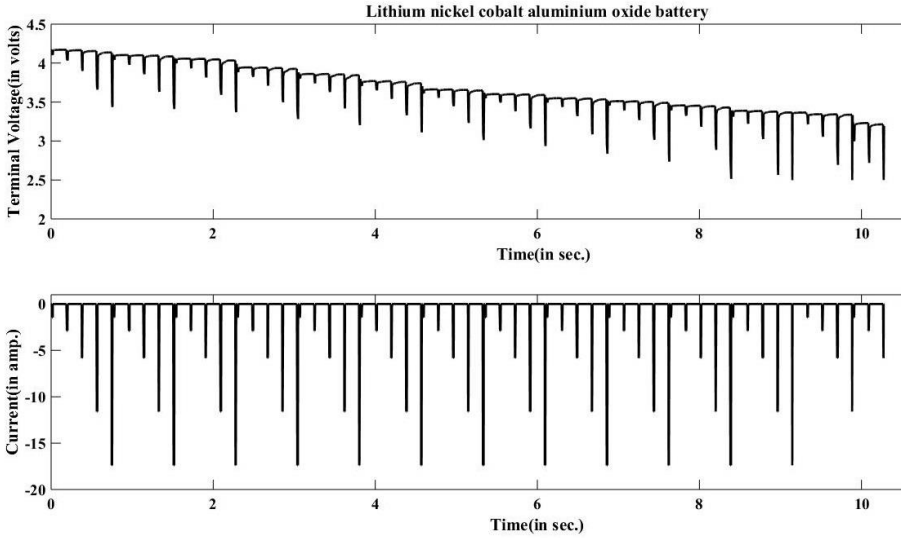

Figure 5: Input and output data of NCA battery.

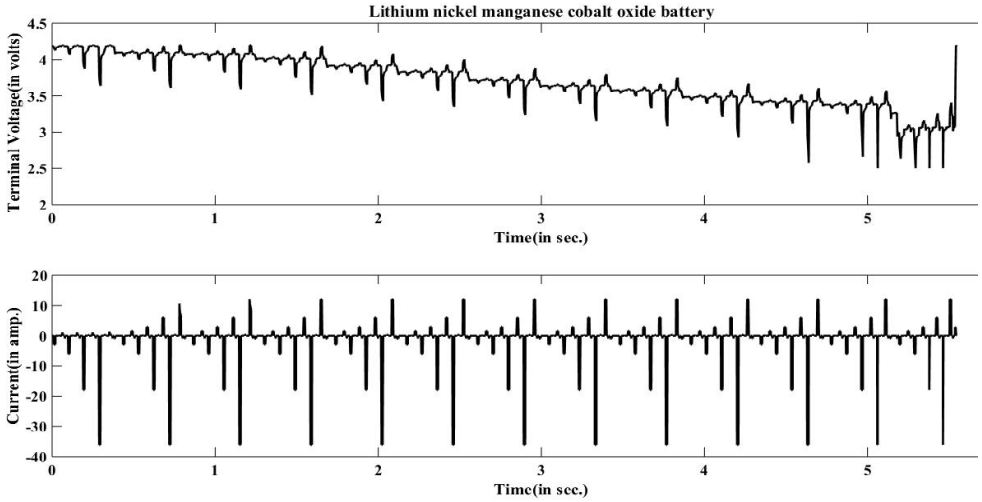

Figure 6**:** Input and output data of NMC battery.

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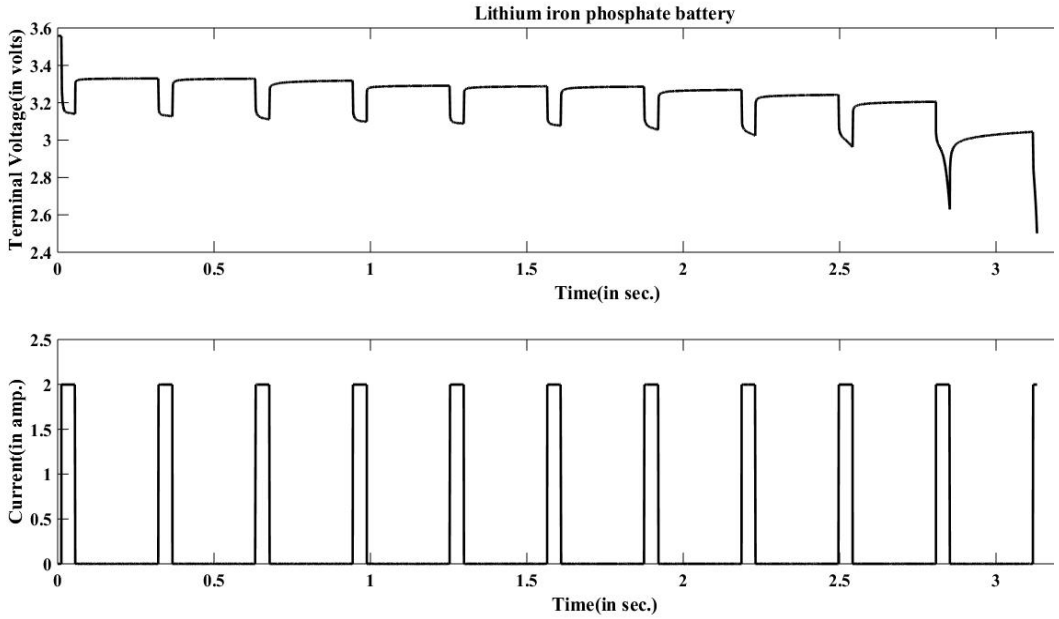

Figure 7: Input and output data of LFP battery.

Results and discussion

The results of the linear *transfer function model* and non-linear *Hammerstein-Wiener model* for the NCA, NMC & LFP battery are discussed in this section. For input-output data 20 iterations in all were performed for each run count to estimate the model's accuracy.

Figure 8 depicts the curves with lowest, moderate, and highest accuracy of the linear transfer function model for NCA battery. The highest model fit accuracy achieved for the linear models was 87.08%, while 81.60% and 59.12% being the moderate and lowest accuracies achieved respectively. The figure 8 also shows that the transfer function model output approaches towards the measured output; however, it fails to capture all battery behavioural dynamics.

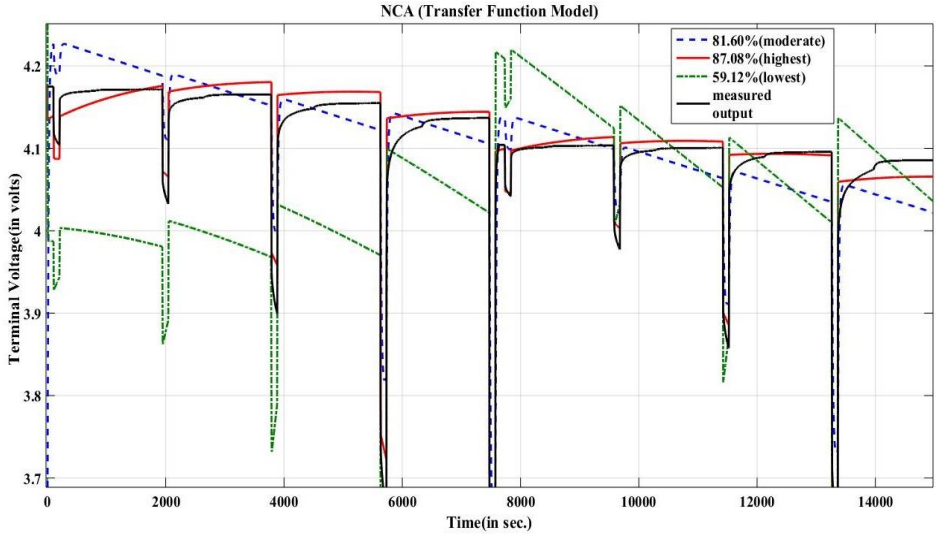

Figure 8: Estimated transfer function models for NCA chemistry.

The figure 9 demonstrates the relative accuracies of Hammerstein-Wiener models identified for the NCA battery type. The highest accuracy achieved for the Hammerstein-wiener non-linear model is 94.15% while moderate accuracy achieved is 75.16% and 3.698% being the lowest.

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The relative accuracies of identified linear transfer function models for NMC battery are depicted in figure 10. The highest, moderate and lowest accuracies achieved for these models are 77.23%, 66.28% and 21.05% respectively.

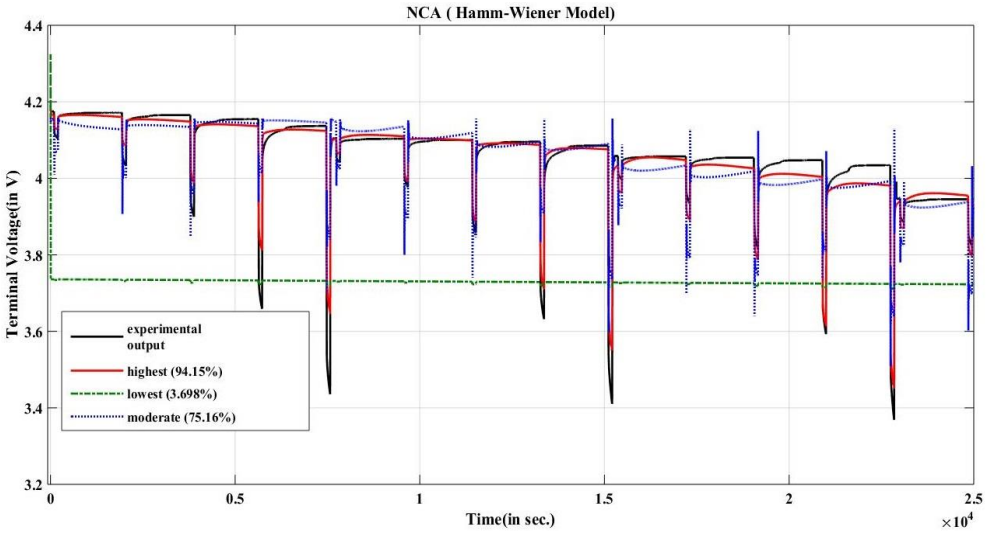

Figure 9: Estimated Hammerstein-Wiener model for NCA.

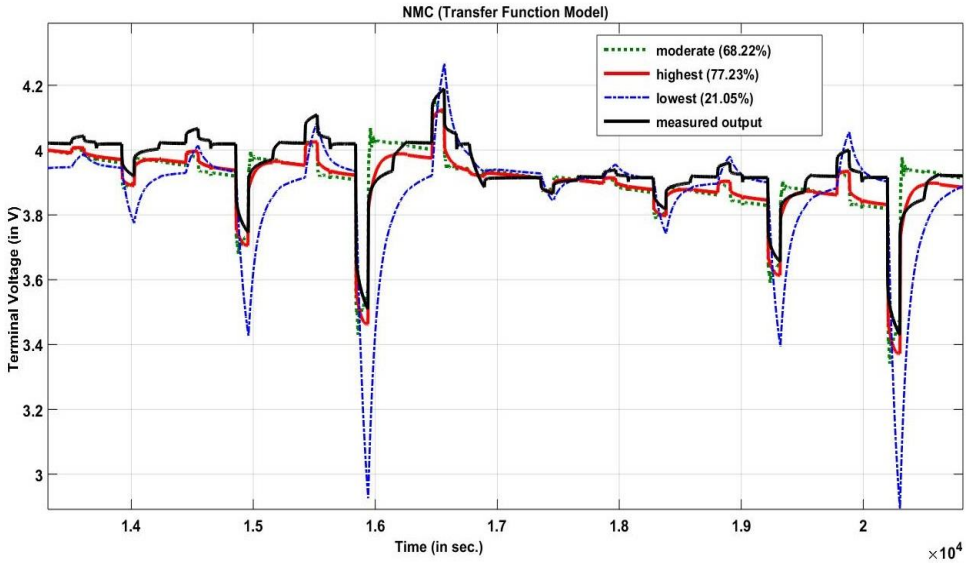

Figure 10: Estimated transfer function model for NMC.

Figure 11 depicts the accuracy levels of the non-linear *Hammerstein-Wiener model*s identified for NMC battery type. Three models were identified with respectively accuracy levels of 94.23%, 66.99% and 16.03%.

Figure 12 depicts the behavioural curves for the achieved accuracy levels in the estimated linear transfer function models for the LFP battery type. The highest accuracy achieved for the transfer function model is only 55.15% while the models with moderate and least accuracy could achieve the accuracy levels of 48.53% and 38.53% respectively. It can also be observed from figure 11 that the transfer function model poorly captures the battery dynamic behaviour and could only achieve nearly 50% accuracy.

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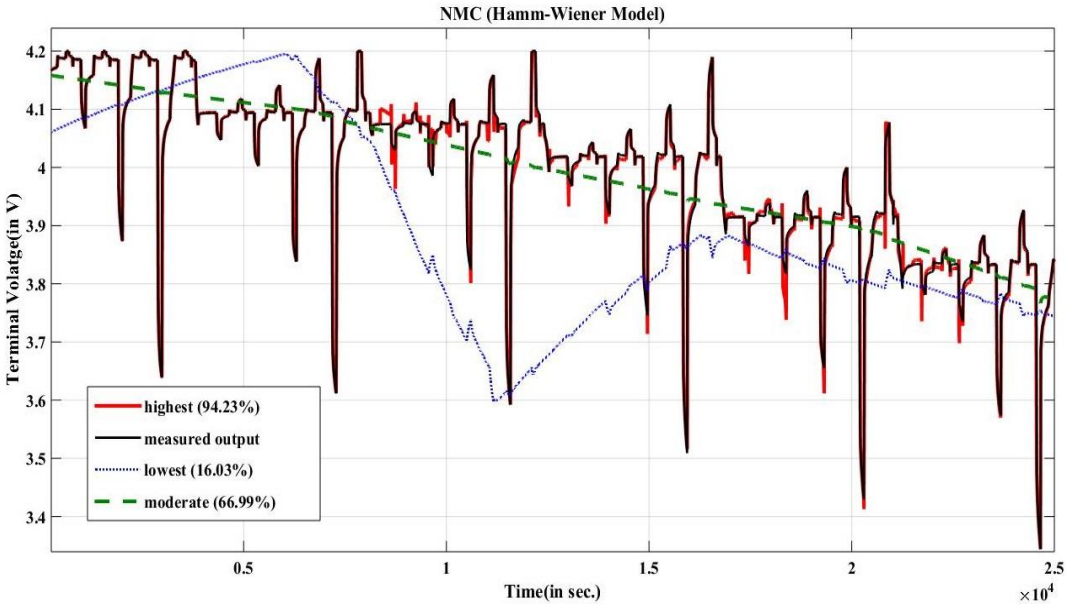

Figure 11: Estimated Hammerstein-Wiener model for NMC.

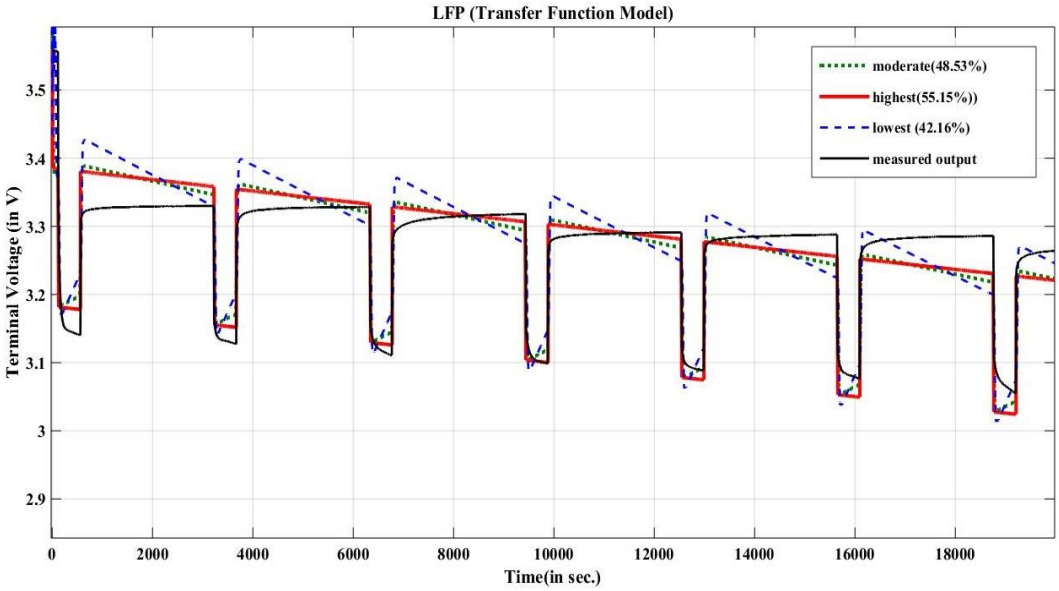

Figure 12: Estimated transfer function model for LFP.

Figure 13 depicts the accuracies of Hammerstein-Wiener model for LFP battery chemistry. The achieved accuracies of the estimated models were respectively 90.78%, 55.8% and 4.829% from highest to lowest. In the case of LFP battery types it can be observed from the estimated models that the non-linear Hammerstein-Wiener models were capable of representing the battery dynamics with relatively much higher accuracy of 90.78% as compared to the linear transfer function model with highest accuracy of only 55.15%.

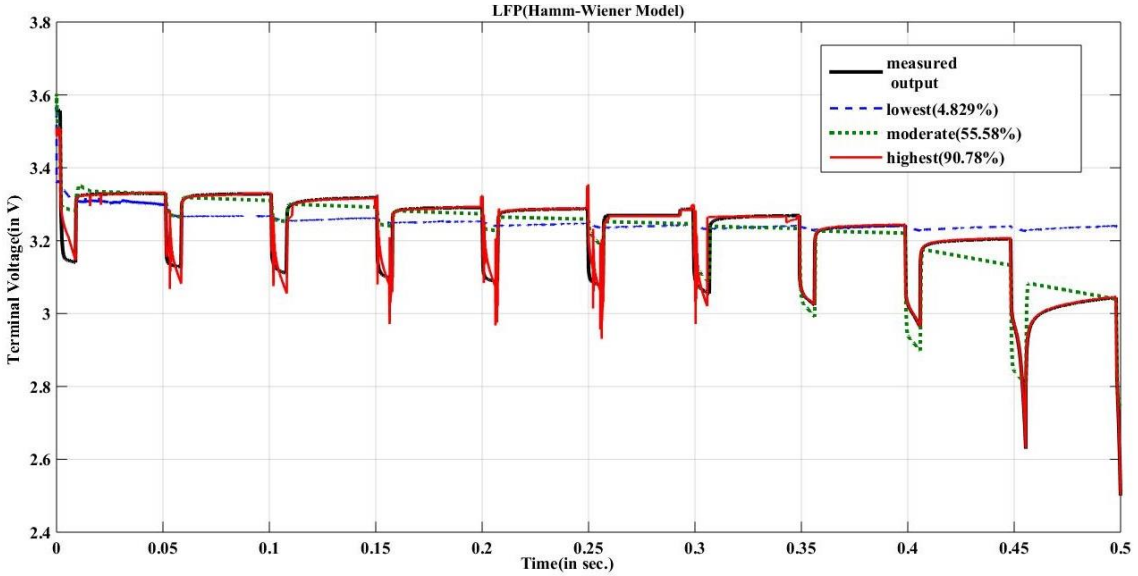

Figure 13: Estimated Hammerstein-Wiener model for LFP.

Conclusion

In this paper the system identification technique was used to analyze and compare the suitability of two models i.e., linear transfer function model and non-linear Hammerstein-Wiener for three Li-ion battery chemistries (NCA, NMC, and LFP). The batteries were subjected to HPPC testing in order to collect data for terminal voltage prediction. MATLAB's time-domain system identification tool was used to load the data set. Using the measured battery current as the input to the models, the terminal voltage for each battery chemistry was predicted. The model fit was used to contrast the two models to select the optimal model for each chemistry.

From the obtained results, it can be concluded that nonlinear Hamm-Wiener model is more accurate in satisfactorily representing the battery behavior for all the three chemistries. The nonlinear model achieves 94.15 % accuracy for NCA, but the linear model could only achieve 87.08 % accuracy. For NMC and LFP the nonlinear model achieved 92.23 % and 90.78 % respectively. Additionally, in the case of a linear model, a deviation occurs for LFP and NMC since the model result could not capture all the battery dynamics during the design process. Hence, it can be concluded that the Hamm-wiener model being the best can be used effectively for representing a Li-ion battery in different applications for BMS.

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