Electric Vehicles Lithium-Polymer Ion Battery Dynamic Behaviour Charging Identification and Modelling Scheme

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Lithium-ion batteries are considered the substantial electrical storage element for electric vehicles (EVs). The battery model is the basis of battery monitoring, efficient charging, and safety management. Non-linear modelling is the key to representing the battery and its dynamic internal parameters and performance. This paper proposes a smart scheme to model the lithium-polymer ion battery while monitoring its present charging current and terminal voltage at various ambient conditions (temperature and relative humidity). Firstly, the suggested framework investigated the impact of temperature and relative humidity on the charging process using the constant current-constant voltage (CC-CV) charging protocol. This will be followed by monitoring the battery at the surrounding operating temperature and relative humidity. Hence, efficient non-linear modelling of the EV battery dynamic behaviour using the Hammerstein-Wiener (H-W) model is implemented. The H-W model is considered a black box model that can represent the battery without any mathematical equivalent circuit model which reduces the computation complexity. Finally, the model beholds the boundaries of the charging process that not affecting on the lifetime of the battery. Several dynamic models are applied and tested experimentally to ensure the effectiveness of the proposed scheme under various ambient conditions where the temperature is fixed at 40°C and the relative humidity (RH) at 35%, 52%, and 70%. The best fit using the H-W model reached 91.83% to describe the dynamic behaviour of the battery with a maximum percentage of error 0.1V which is in good agreement with the literature survey. Besides, the model has been scaled up to represent a real EV and expressed the significance of the proposed H-W model.

Keywords: Electric vehicles, Battery identification, Hammerstein-Wiener, Lithium-polymer ion battery, EV fast charging

Introduction

Lithium-ion batteries (LIBs) with all categories have been extensively utilized for most electronic equipment and massively in Electric Vehicles (EVs). LIBs are commercialized because of their high energy concerning their size, long lifetime span, high efficiency and low rate of self-discharging[1]. Due to the non-linear behaviour of the LIB while charging, and the variety of the input parameters which affect the charging process such as charging current, and ambient conditions represented by temperature and relative humidity, an accurate identification model of its dynamic behaviour is required [1].

The environmental temperature has a main impact on lithium-ion batteries' charging and discharging operations. The recommended ambient conditions were suggested to be from 20°C to 45°C. Exceeding the upper limit may lead the battery to an acceleration in the capacity degradation rate and thermal hazards[2]. The temperature and capacity rates are influencing the degradation rate of the battery. In the range from 10°C to 60°C, the degradation rate raised while implementing low C rates. Despite of this, the degradation at 45°C is lower than that at 25°C while utilizing the 2C rate. It is concluded that each temperature and C rate have its own characteristics and battery representation[3]. In [4, 5], the charging operation of the lithium-polymer ion battery is investigated at different ambient conditions to recognise and classify the EV. In [6] the authors demonstrated that the operation of the Li-O_2 batteries has been affected by the humidity where the water can collapse cyclic and rate abilities. Consequently, EV batteries' robust monitoring and modelling are required at any ambient condition to represent the non-linear dynamic behaviour and avoid the hazard of fast charging. The variation in ambient conditions created a direct need for an efficient and accurate non-linear representation of the EV battery's performance.

Models of the LIBs could be assorted into two major classes: the electrochemical (EC) and the electrical equivalent circuit (EEC) models. The EC model represents the physical-chemical internal reactions inside the battery[7, 8] and the EEC model expresses the battery through electronic parameters such as resistors and capacitors. The equivalent circuit models can be categorised into the Rint model, Partnership for a New Generation of Vehicles (PNGV) model, and RC transient models which are branched from the 1st-order to nth-order transient model [9-12]. In [13] electrical equivalent circuit models from 1RC to 5RC transient models have been used to describe the LIB. The parameters are evaluated at various temperatures of 0°C, 25°C, and 45°C. The 3RC EEC model ensured optimum accuracy and minimum error of 1.8% using the non-linear least square algorithm. In [14], the Electrothermal modelling of lithium-ion batteries has been investigated by 1RC ECM. In addition, the battery's internal parameters at different temperatures and current rates have been investigated. An improved reduced-order electrochemical model (IROEM) is proposed in [15]. In [16] a novel mesoscale electrothermal modelling is presented. In [9, 17-19] the 2RC transient circuit has been used in modelling the lithium-polymer ion battery, however, multi-experimental procedures are accomplished to calculate the EEC model components such as ohmic internal resistance, and electrochemical and concentration polarization resistances and capacitances.

The variety of the ambient conditions represented by the temperature and relative humidity created a direct need for an accurate model of the LIB with a minimum percentage of error and high accuracy to describe the battery in any environmental circumstances. The EV battery modelling research area is directed to focus on the system identification methods [20-22] which were dealing with the battery cells as a nonlinear dynamic behaviour like most real systems. Hence, the white box model and black box model are utilized to express the systems [23]. In [24] the Adaptive Neuro-Fuzzy Inference System (ANFIS) model is utilized to express the LIB and is considered a black box model. In [25], Hammerstein-Winer (H-W) model ensured the best fit of 89.79%, 93.53%, and 94% for representing the LIB at various driving cycles while the temperature is fixed at 25°C. In [26], the authors used Polynomial and H-W models for both the charging and discharging cycles to ensure higher accuracy. However, the maximum error using the H-W and polynomial models reached 10.6% and 10.8% respectively. In [27], the components of the 2RC model have been identified using both the continuous and discrete time models. In [28] mathematical models are used to calculate the LIB's unknown coefficients for efficient monitoring and quick charging. However, the forementioned models didn't represent the dynamic behaviour of the LIB under any environmental conditions. This paper suggests a clear framework for expressing the lithium-polymer ion battery's non-linear charging operation by monitoring the surrounding environmental circumstances. This is followed by a set of recommendations for the EV's user to avoid overcharging current and voltage.

Methodology

An approach for monitoring the electric vehicles' battery dynamic behaviour is proposed in this article. This scheme consists of multiple stages as shown in Figure 1; Firstly, the influence of various environmental conditions on the charging operation of the lithium-polymer ion battery is investigated. Then sufficient identification and modelling of the battery are obtained through full monitoring of the battery's dynamic behaviour at any ambient condition. Finally, a user guide of the charging boundaries is suggested based on the battery dynamic model to alleviate the degradation rate of the battery and avoid hazardous operations.

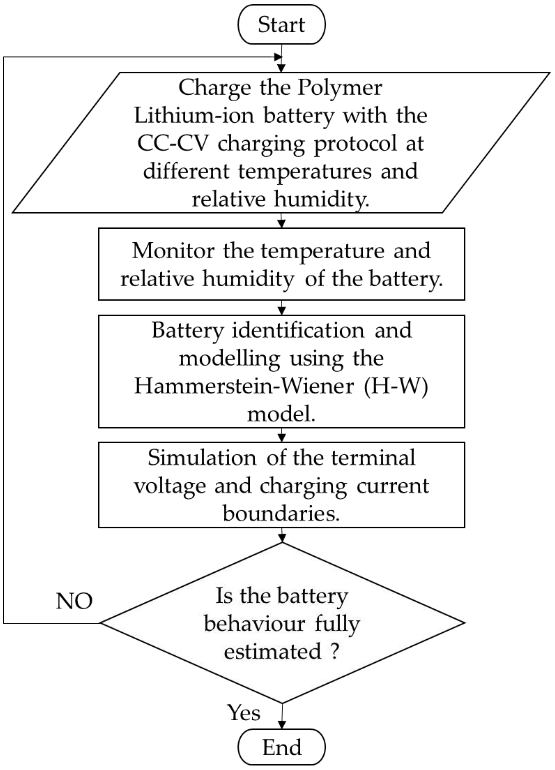


Figure 1. A flowchart of the proposed approach.

Hammerstein-Wiener (H-W) Identification model

Instead of the electrochemical and electrical equivalent circuit representation models, Hammerstein-Wiener (H-W) identification model is implemented to express the output nonlinear performance of the LIB. It is extensively utilized in nonlinear industrial systems [29]. This model is composed of a nonlinear block which is called the Hammerstein model followed by the linear block which is called the Wiener[30]. The main stages of the H-W identification model are represented in Figure 2. The procedure of these stages is started by converting the non-linearity experimental input data to a dynamic linear block which is called the Hammerstein model. This is followed by the Wiener model which converts the linear model to the output non-linear required results. The main equations are expressed in [23, 30, 31] and presented as follows

$$w(t) = f(u(t)) \tag{1}$$

$$x(t) = \frac{B}{F} w(t) \tag{2}$$

$$y(t) = h(x(t)) \tag{3}$$

Where $w(t)$ and $x(t)$ are the input and output of the dynamic linear block respectively and $y(t)$ is the output of the H-W identification model.

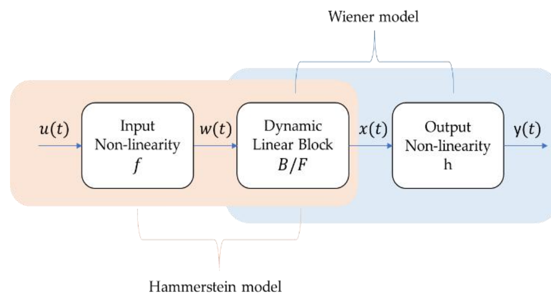


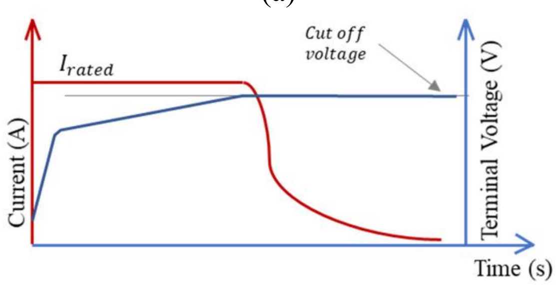
Figure 2. Schematic representation of the H-W identification model[4].

Data collection

In this study, the EV is presented by a small-scaled lithium-polymer ion battery of 1,000 mAh with a working temperature from 0°C to 40°C, and the charging and discharging cut-off voltage of 4.2±0.05 V and 2.75V respectively.

The influence of varying the temperature and relative humidity on the charging operation is scrutinized by testing the battery in different ambient conditions using a controlled chamber as in our previous research articles[4, 5] and presented in Figure 3-a. The constant current stage followed by the constant voltage stage (CC-CV) charging protocol is used to charge the battery as shown in Figure 3-b. The battery's VI characteristics (charging current and the corresponding terminal voltage) are scrutinized at 30°C and 40°C while fixing the RH of 52%. The temperature/RH sensor used is the DHT11 and located inside the chamber and far from the lithium-polymer ion battery under the test by almost 2 cm.

(a)

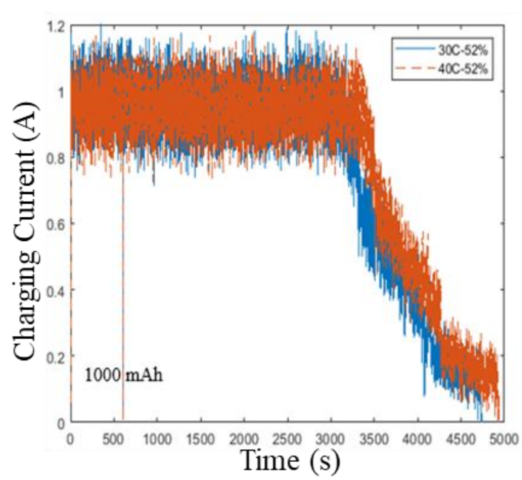


(b)

Figure 3. (a) The proposed test rig and (b) the CC-CV charging protocol [4, 32].

It is observed that the battery is fully charged at 4,742sec and 4,919sec at 30°C and 40°C respectively as shown in Figures 4-a and 4-b. Hence while raising the temperature the charging time is increased. In addition, another test has been performed on the battery while maintaining the temperature at 40°C and varying relative humidity. The interval time required for the battery to reach full capacity is 4,606sec, 4,938sec, and 5,690sec for the RH of 35%, 52%, and 70% respectively as shown in Figure 4-c and 4-d. Hence whenever the RH is increased the charging time is increased. In addition, as declared in Figure 4-c the charging process could be split into the CC stage and CV stage. Whenever the RH increased the interval time of the CC stage becomes very short with respect to low RH conditions. However, the CV stage took longer interval time than the low RH conditions. Consequently, high RH directs the lithium-polymer ion battery to take more time while charging.

Based on the proposed experiments, it is observed that whenever there is any change in the ambient conditions represented by temperature or/and relative humidity, the charging pattern differs from one case to another, so a sufficient lithium-polymer ion battery identification model must be obtained. In this paper, the H-W identification model is used to represent the dynamic performance of the battery under any circumstances as will be scrutinized in the following sections.



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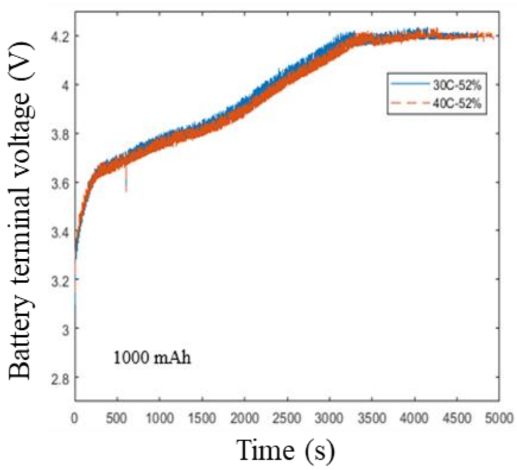

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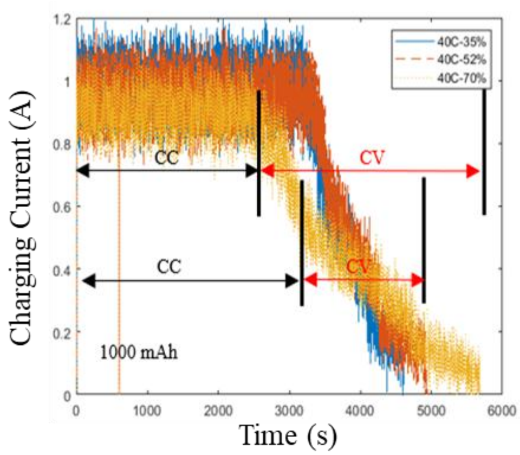

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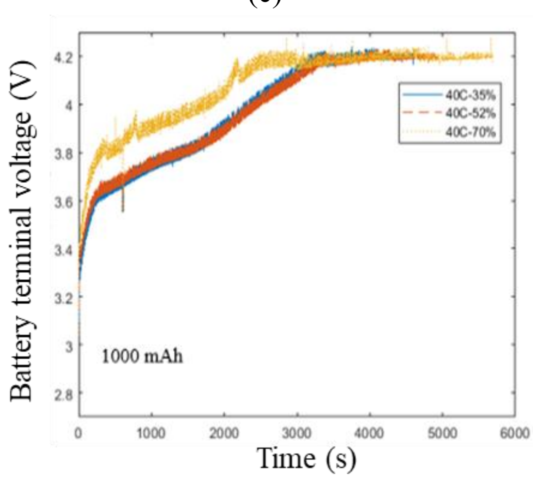
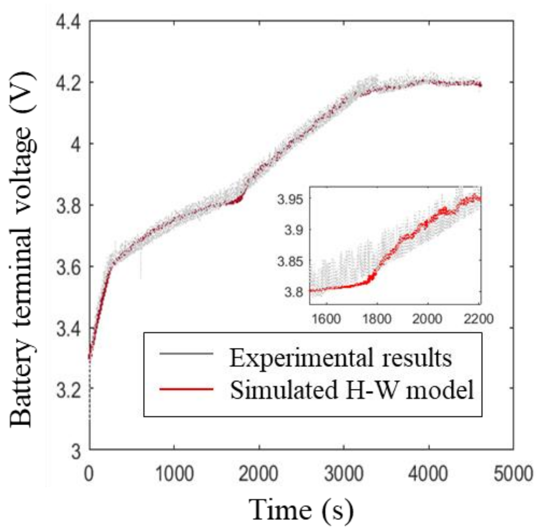


(d)

Figure 4. The charging VI characteristics of the utilized battery (a), (b) at different temperatures of 30°C and 40°C while maintaining the RH constant at 52%, (c), and (d) at various RH of 35%, 52%, and 70% while maintaining the temperature constant at 40°C [4].

EV battery dynamic behaviour modelling

The H-W identification model has been used to estimate the dynamic performance of the lithium-polymer ion battery with a model structure of one numerator order and three denominator order utilizing various search methods. Three ambient conditions of the battery have been utilized in this study where the temperature is kept constant at 40°C and the RH is varied to be 35%, 52%, and 70%. The CC-CV protocol is used with a current stage of 0.9A to charge the lithium-polymer ion battery in all conditions. The relationship between the experimental and simulated model output using the H-W identification model of all conditions is presented in Figure 5. Each charging process at a specific ambient condition could be represented with different VI characteristics (charging current and the corresponding battery's terminal voltage) which will be reflected in the interval time. Consequently, the H-W identification model tries to represent the battery's dynamic performance in any environmental condition and tracks all the curvatures on the graph to reach the optimum fit of performance. The best-fit results for all the mentioned conditions are 90.98%, 91.83%, and 82.24% respectively using the Levenberg-Marquardt(LM), Gauss-Newton(GN), and Adaptive Gauss-Newton(GNA) search methods respectively. The selection of the search method is automatically performed using the Matlab/SIMULINK Program to reach the optimum solution.



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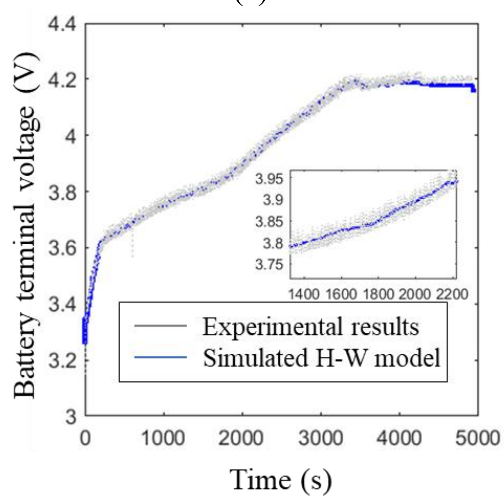

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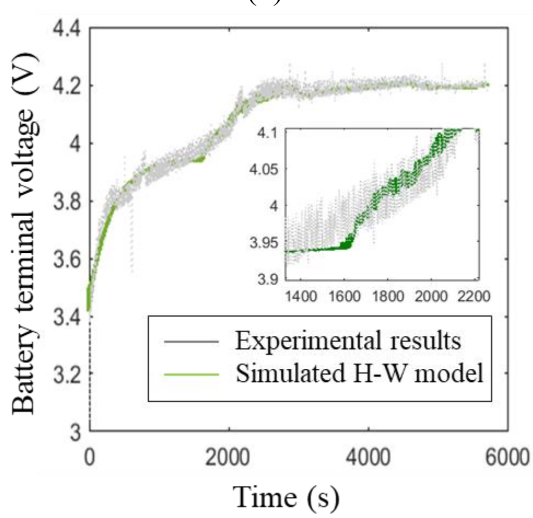
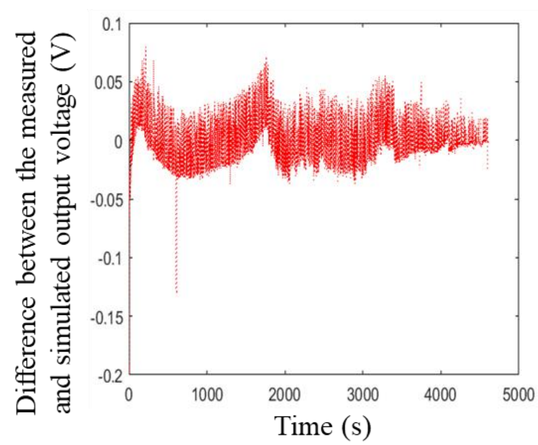


(c)

Figure 5. Battery identification and modelling using the H-W identification model of 1,000 mAh lithium-polymer ion battery at different RH of 35%, 52%, and 70% respectively while maintaining the temperature at 40°C.

Hammerstein-Wiener (H-W) model Validation

The effectiveness of the suggested non-linear identification model is presented in Figure 5 which declares the variance between the experimental and simulated battery terminal voltage for each ambient condition. The battery's terminal voltage error at a specific temperature of 40°C and various RH of 35%, 52%, and 70% reached almost 0.05V, 0.05V, and 0.1V respectively which is almost equivalent to 1.35%, 1.35%, 2.7% of the battery nominal voltage (3.7V) as observed in Figure 6 respectively. These values prove the good performance of the H-W identification model concerning the literature survey[26].



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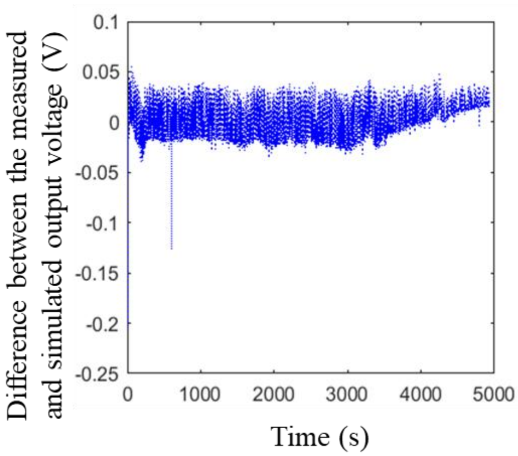

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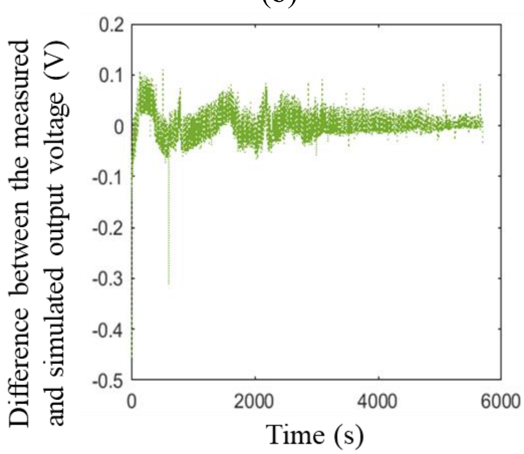


(c)

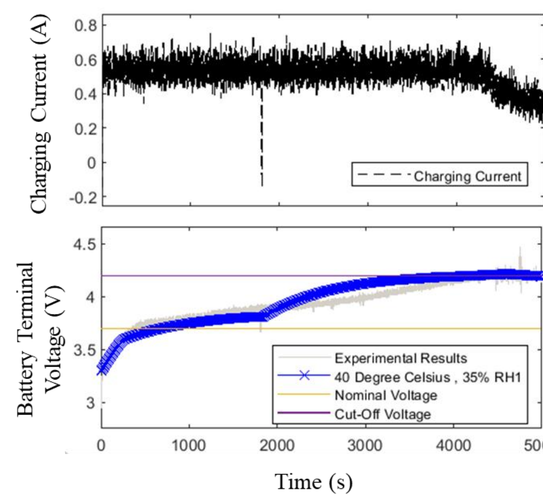
Figure 6. The variance between the experimental and simulated battery's output terminal voltage at a fixed temperature of 40°C and different RH of 35%, 52%, and 70% respectively.

The results that represent the battery dynamic behaviour identification best fit, the search method using the H-W model and the terminal voltage error at different ambient conditions have been represented in Table 1.

Table 1. Battery identification comparative study at different ambient conditions using the H-W model.

Ambient condition (Temp, RH)	Best fit (%)	Terminal voltage error (V)	Search method
40°C, 35%	90.98	0.05	LM
40°C, 52%	91.83	0.05	GN
40°C, 70%	82.24	0.1	GNA

To validate the H-W model the temperature is fixed at 40°C and the RH at 35%. The battery has been charged by the CC-CV charging protocol by 0.5A where the terminal voltages of the simulated and measured battery are expressed in Figure 7-a. In addition, Figure 7-b declares the output difference between the modelled and experimental representations, ensuring the high performance of the suggested model where the maximum error reached 0.176 V which is equivalent to 4.757% of the battery nominal voltage (3.7V).



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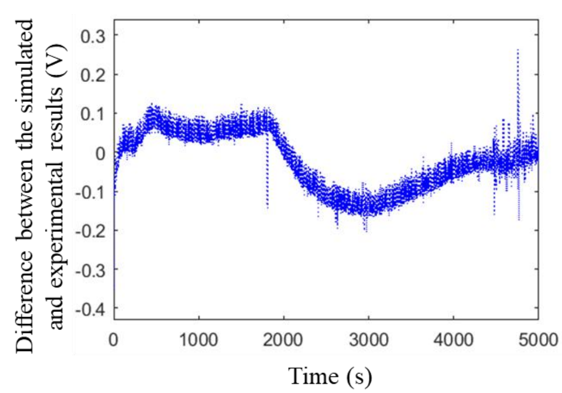


(b)

Figure 7. H-W model validation at 40°C

and RH at 35% (a) the charging current using the CC-CV and Terminal voltage of the simulated and measured results and (b) the variance between the experimental and simulated outcomes.

The final stage of the presented model depends on the sufficient identification model estimated in the previous stage. This stage expresses the permitted charging current and output terminal voltage of the battery at any ambient condition to prevent battery degradation and avoid any hazardous operation.

Comparative Study

As shown in Figure 8, the output battery terminal voltage while charging by 0.9A is expressed throughout the three mentioned conditions. The batteries reached the nominal voltage after 635.465sec, 750.423sec, and 220.337sec respectively. Besides, the 3rd case study which represents the battery at 40°C and RH of 52%, reached its cut-off voltage at 2,111sec. Hence whenever you exceeded the permitted battery's terminal voltage, you accelerate the degradation factor rate and shorten the cycle life which may cause the battery's hazard.

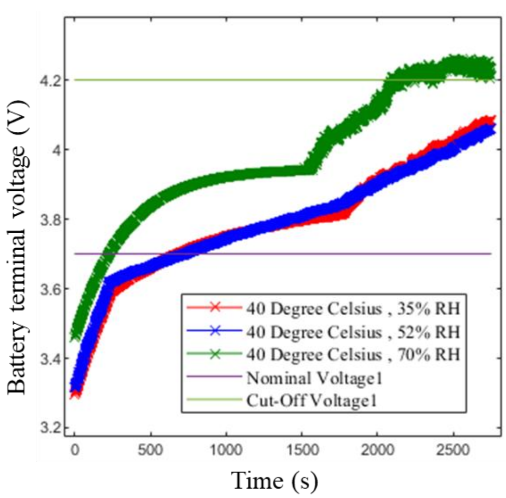
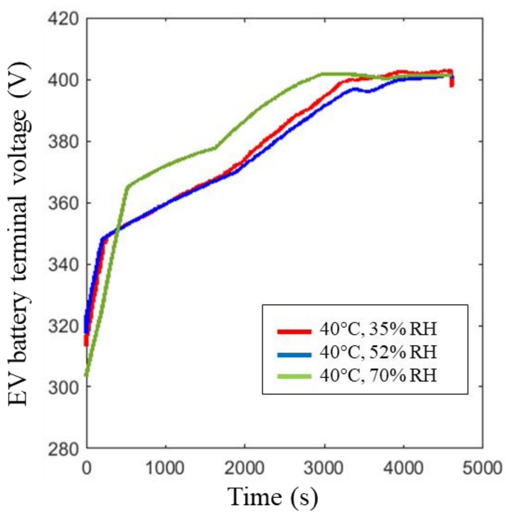


Figure 8. The output terminal voltage while charging by 0.9 A on the proposed H-W identification models at the proposed ambient conditions.

EV Lithium-ion Battery Scaling-Up Representation

In this section, the lithium-polymer ion battery is scaled up to match the 2015 Chevrolet Spark EV specifications [32]. This category uses the LG Chem lithium-ion battery with a nominal cell voltage of 3.7V, a nominal system voltage of 355.2V, and 192 cells of 6 modules. In our case study, we will implement the same configuration with our lithium-polymer ion battery of 1,000 mAh to investigate the importance of the H-W identification model in any environmental condition. However, the internal heat impact of the cells on each other was considered constant in the proposed model. The utilized modules in real EVs are specified with high energy capacity rates reached to 200kAh [32]. In our case study, we used a lithium-polymer ion battery with a 1,000 mAh battery capacity to format the module. The EV battery is composed of 16 cells in series and parallels with another 16 series cells to format the module. This category has 6 modules in a series connection.

Three H-W identification models are implemented as shown in Figure 9-a. The scaling-up ensured the best fit of 90.3%, 91.23%, and 83.37% for the mentioned case studies respectively. The EV battery terminal voltage variance between the simulated and scaled-up data reached 5V, 5V, and 7V respectively which means an error of 1.4%, 1.4%, and 1.97% respectively with respect to the nominal voltage of the battery (355.2V). This representation is based on the assumption that the ambient conditions of the battery's pack are the same as the 1,000 mAh battery used in the previous sections. As observed in Figure 9-b, the three conditions have been charged with the same charging current and reached the nominal voltage in 547.958sec, 690.903sec, and 207.611sec respectively. In addition, the 3rd case study reached the cut-off voltage (403.2V) in 2,719sec however the other cases did not reach the upper limit till the end of the simulation time 2,750sec. the degradation rate will be increased when you exceed the cut-off voltage as mentioned in the literature survey.



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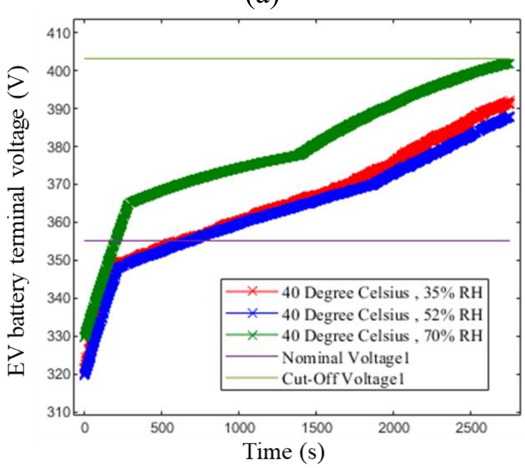

(b)

Figure 9. The EV battery terminal voltage after scaling up at various ambient conditions.

Conclusion

A novel schematic charging framework based on the monitoring and modelling of the lithium-polymer ion battery is suggested and investigated in this article. A non-linear black-box model for a lithium-polymer ion battery of 1,000 mAh is proposed based on the Hammerstein-Wiener (H-W) identification model. The nonlinear H-W model represented the EV battery's electrical dynamic behaviour at different environmental circumstances of temperature and RH. The proposed model ensured the best fit of 90.98%, 91.83%, and 82.24% for different ambient conditions with a maximum error of 0.05V, 0.05V, and 0.1V respectively. A comparative study between the different models has been established while charging by the same current to indicate the importance of accurate modelling accompanied by the minimum percentage of error. In addition, a scaling-up case study is proposed based on the EV battery specification in the market. This could be a smart warning flag for the EV's user while charging to improve the storage security, safety operation, and battery management performance. The proposed model could be supported by artificial intelligence (AI) algorithms to estimate all the required models at the remaining ambient conditions.

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