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Study of estimation of battery state of charge (SoC) and state of health (SoH) using neural network techniques

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I would like to dedicate this thesis to my love Wan Hongxing for support and accompany me through all the difficult time . Her belief in me has kept my motivation during this process and. Her encourage has brought me enormous strength to across every step.

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I would also like to thank my friends and family who supported me and offered deep insight into the study.

Abstract

Nowadays the electric vehicle(EV) has become the main development direction for all OEMs, to meet the challenges of environment and energy saving. The core factor which leads the development and performance of electric vehicle is the use of Lithium battery, that varies the available range of vehicle and its power performance.

Various Lithium-ion battery has been introduced into market leading different performance characteristics with increased energy density. From development point of view, different battery development direction requires a reliable system for control and monitoring the status of the battery.

This thesis addresses to compare via the modelling approach using an equivalent circuit battery plant with extended Kalman filter and neural network method from machine learning approach to present a robustness result of battery condition estimation comparison.

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1. Introduction

Nowadays, the most popular battery group can be divided into 2 major types, Lithium-ion batteries power things like our phones and electric or hybrid vehicles, and lead acid batteries that are used to start cars with internal combustion engines and store power for the car's lights, radio, and other devices [3][4]. The main driving factor for using Li-ion battery on automotive field is the high energy density. That's why lithium-Ion batteries are used in so many applications and are replacing lead acid batteries for things like transport and grid applications. Electric vehicles' production is increasing and EVs are becoming more popular due to their zero-emission and high tank-to-wheels efficiency.

1.1 Importance of Electrical Vehicle Battery

For EV Vehicle applications that require an accurate and dynamic prediction of the battery performance, a battery model is usually incorporated in the battery management system(BMS) [1]. The following mean characteristics of EV vehicle battery have normally been taken into development considerations:

- **Density:** The amount of energy that a battery can store in relation to its weight. The greater the density, the greater the storage capacity and the longer the vehicle range. It is expressed in W.h/kg (watt-hours per kilogram).
- **Voltage:** The power that the battery can supply per kilogram of weight of the battery, which is therefore expressed as W/kg (Watts per kg). The greater the power, the greater the performance of the vehicle.
- **Efficiency:** The performance of the battery can be described to the capability of deliver energy into the charging and discharging process. The healthier the battery is, the more capacity it contains.
- **Life cycle:** The number of times that a battery can be charged and drained before needing replacement, since they lose capacity. The more cycles the battery has, the longer it will last.

Balancing a lithium battery pack correctly is one of the most important functions of a BMS system. This process is crucial to ensure maximum efficiency and the highest capacity throughout the battery's entire life cycle [3].

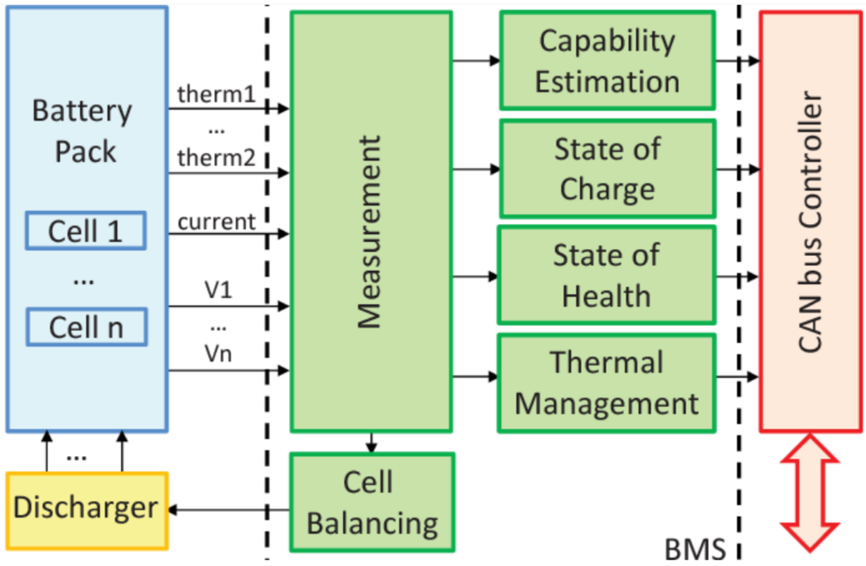


Figure 1. BMS function to Vehicle level

Refer to figure 1. BMS functions ensures stable performance of a battery over time, prevents faults, and provide battery state diagnostics which is the core management for an EV vehicle [2].

- Real time monitoring of every battery parameter
- Sending battery info (SoC, SoH, other battery signals etc.) to the vehicle control unit, motor control or on-board display
- Controlling the battery charger
- Heating and cooling the lithium battery pack
- Performing predictive analysis throughout the life of the vehicle

From the above function, one can understand that it is necessary to ensure the accuracy of the battery performance in real-time as much as possible to monitoring the battery aging, battery charge and discharge condition to extend the battery lifetime by preventing over (dis)charging via BMS control and to increase the reliability of these systems [1][5].

From the figure 1. Sate of charge (SOC) and State of health(SOH) accurate estimation are one of the most important functions in a battery management system.

State of charge (SOC)

The SOC is an indication of the amount of energy available in the battery compared to its maximum capacity, and this makes it very similar to the fuel gauge in its concept [3].

For the battery cell, an accurate SOC can provide precise parameters to make a batter lithium-ion battery cell. For the EV battery systems, an accurate SOC can prevent the battery from over-discharge and charge, thus ensuring battery system safety, making more efficient use of the limited energy, and extending the battery life [7]. The accurate monitoring of SoC supports the battery management system the general control condition as key status of the battery model. The units of SoC are normally given in percentage points (0% = empty; 100% = full)

State of Health (SoH)

The SOH is an indication of the battery current condition compared to its new condition. It describes the difference between battery capacity on used and fresh battery that leads to the cell aging, the expression of SOH has been defined as the ratio of the maximum battery charge to its rated capacity in percentage [4]:

$$SoH(\%) = 100 \times \frac{Qmax}{Cr}$$

Cr = The rated capacity

Qmax(Ah) = The maximum charge available of the battery

Like most mechanical/electrical systems, the performance of lithium-ion battery indispensably degrades with operation. To be specific, the battery capacity declines, and its resistance increases when the battery ages.

1.2 Estimation difficulty for Li-Ion application

Lithium-ion batteries are considered the most promising power sources for EV due to their high power and energy densities [3]. Li-ion technology introduce a flat discharge curve, long-life cycle, and high energy density characteristics keeping the voltage stable up to 80% of discharge time, which makes it very difficult to estimate SoC on a simple voltage measurement for its non-linearity. The voltage difference between two SoC values may be so small that it is not possible to estimate the state of charge with good precision [2][4].

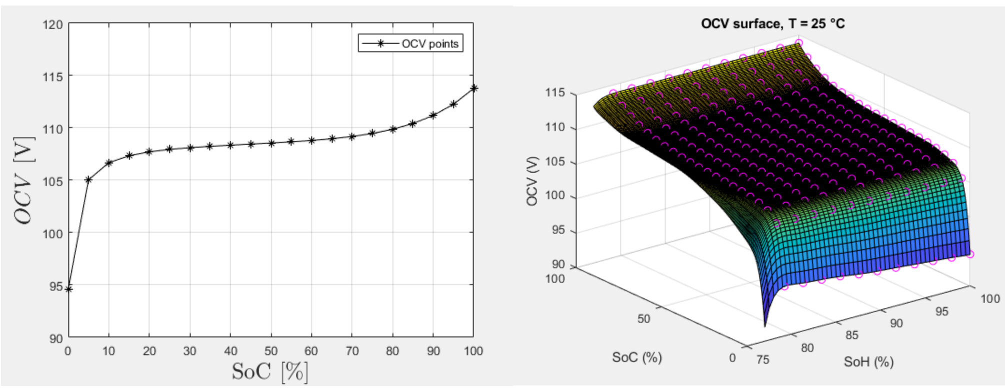


Figure 2. Reference OCV-SOC(SOH) curve of Li-Ion battery

Refer to the figure 2, we can notice the challenges of Li-ion battery condition accuracy occur.

- Long voltage relaxation time to reach its open circuit voltage (OCV) after a current pulse.
- Temperature and SOC dependence with Flat OCV-SOC curve for most of the SOC range.
- Precise measurement of initial condition from unknown condition due to internal resistance loss can been observed from figure 3. This will lead into an unknown status for unknown battery where its initial state is necessary to be studied.

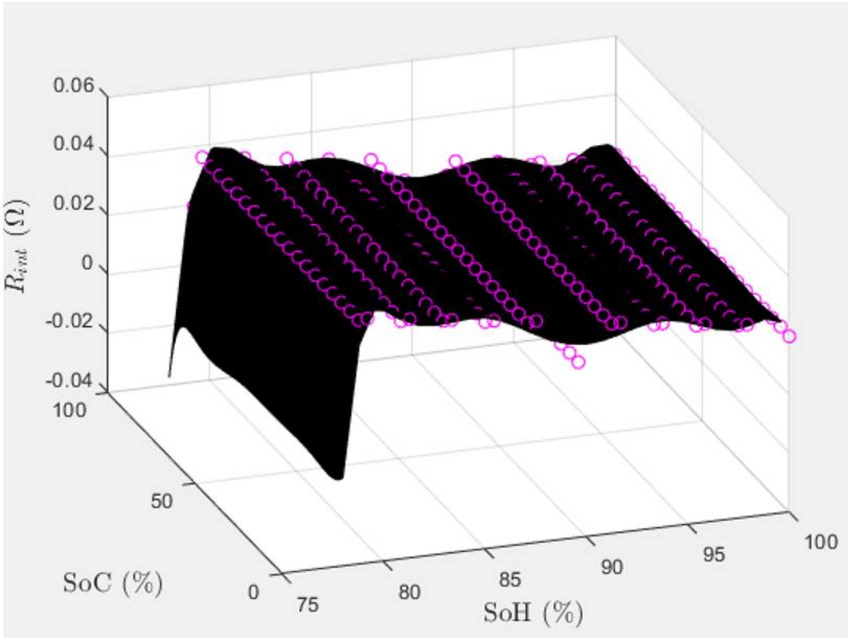


Figure 3. Reference internal resistance variation vs. SOC&SOH

- Due to battery aging, SOC could not be accurately estimated as well. Degradation of internal resistance and capacitance, and available power fade are the main factors leading to battery aging. Main aging causes for Li-ion batteries are the decomposition of solid electrolyte interphase (SEI), deposition at the anode, metal dissolution from the anode, the loss of active material, and lithium plating [7]. The analysis of the reasons for battery aging is shown in Figure 4.

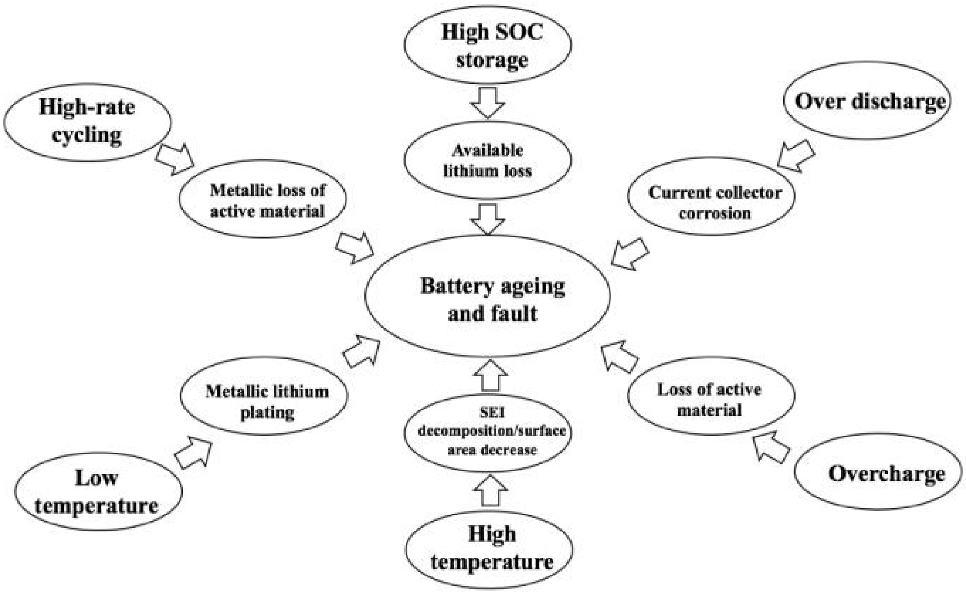


Figure 4. Analysis of the reasons for battery aging[7]

The most widely used SOC estimation algorithm in the battery management system of electric vehicles is a hybrid algorithm based on the combination of the equivalent circuit model and the Kalman filter algorithm family. The most significant error source of this method is that the voltage and current sensor drifts the battery model shortcoming, for which the influence of the variable effect are not enough, for example, the aging, temperature, and hysteresis effect [7].

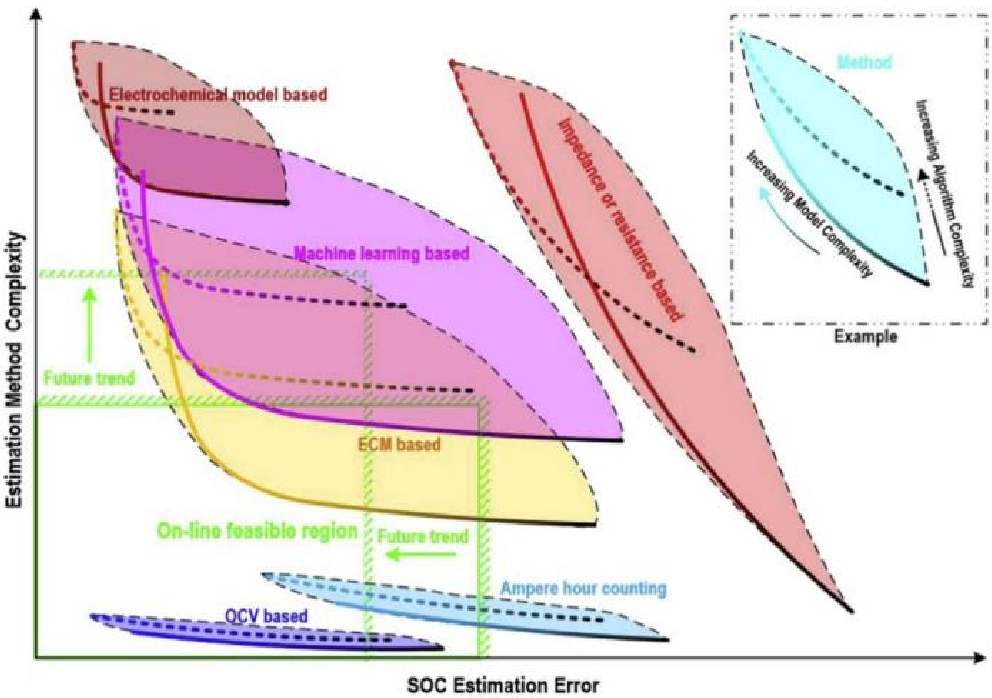


Figure 5. Estimation error and computational complexity for the commonly studied SOC estimation[34]

According to the previous study, from Figure 5 it demonstrates the estimation error and computational complexity of the SOC estimation methods among different approaches. In this study, the most focus will be put into the modeling method using Extended Kalman filter(EKF) with Equivalent circuit model(ECM) of battery in simulation environment compare with the neural network method (machine learning approach).

1.3 Measurement approach

Followed from Figure 4. several methods that has been used to estimate the SOC ranging from simple to sophisticated methods with different error margin. Those methods can be classified into two types: direct and indirect [9]. Here in this study the SoC estimation on a system level is always based on estimating the SoC of single cells [6].

Traditional approach normally taken as direct methods, like Ampere-hour method and Coulomb Counting method uses discharge current integration to estimate SOC which is the easiest method and can be implemented with low power consumption [14]. However, the method suffers from difficulties in determining the initial value of SOC which causes a cumulative effect. Open Circuit Voltage (OCV) is another frequently used direct method approach which achieves high accuracy in SOC estimation [15]. Nevertheless, OCV needs long duration before it reaches a stable condition.

There are several indirect methods that are used to estimate the SOC. Those methods can be very accurate and reliable in general. Among those methods are extended Kalman filter (EKF) and artificial neural network (ANN) [9].

Modelling approach is usually implemented by using ECM with Kalman filter method, which can reduce the high extent of noise in current measurements and offers a computationally efficient option for runtime SOC evaluation on-board vehicles [10]. An ideal ECM should be able to simulate the actual battery voltage under any current excitation. However, some characteristics of the lithium-ion batteries cannot be well represented by circuit elements, such as the hysteresis effect or the Warburg effect. This method requires high mathematical computation and is extremely vulnerable to aging, temperature, and highly non-linear system[6].

In contrast, ANN methods don't rely on any electrical, physical, chemical, or thermal model [5] and they require less computation capability compared to EKF methods which represents a new solution with less complex modelling requirement for having more efficient development effort. The artificial neural network (ANN) has the self-learning skills and adaptability to demonstrate a complex non-linear model. This approach uses the training data to estimate SOC without knowing information about the internal structure of the battery and initial SOC information. Through this thesis the capabilities of both EKF- and ANN-based methods in estimating the SOC and SOH will be studied.

2. Modeling of Battery

The model-based estimation consists of two major parts: a battery model and an estimation algorithm [5]. In the model-based estimation structure, a battery model is established to predict the terminal voltage, and the current, SOC, and temperature are the usual inputs.
The equivalent circuit model (ECM) is used to describe the cells' behavior. Compared to other models, such as physical models, ECM offers low computational complexity and requires a small number of parameters, and still provides good approximation [12].

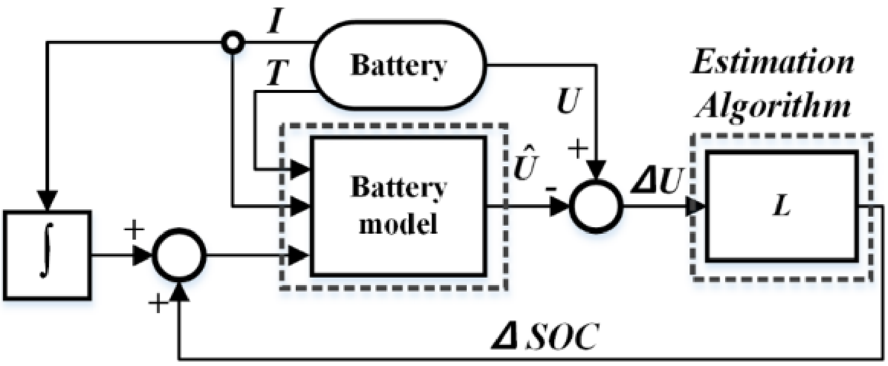


Figure 6. Framework of the model-based State of Charge (SOC) estimation methods

From previous studies which contains different ECM structure analysis indicate that two RC ECM is an optimal choice for the energy storage system and one RC ECM with hysteresis voltage is preferred for battery with strong hysteresis effect in the terminal voltage. Therefore, adding more RC networks generally improves the modeling accuracy, but having more than two RC networks also increases the computational burden [5].

For the following study in simulation environment , a dual RC ECM has been build using only reference battery data has been built to validate the approach algorithm. While by validation and experimental phase, a single pair RC ECM validated with actual battery will be replaced for adapting to real test condition.

2.1 Model equations

The dual RC model introduced as Figure 7 with implemented battery model dynamics is predicted by a model with a second-order resistance-capacitance circuit network [13].

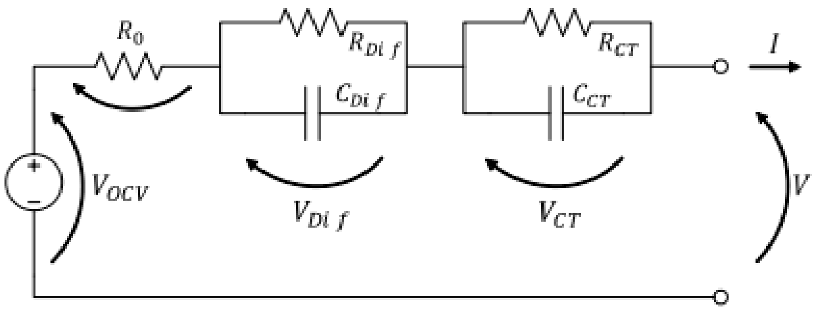


Figure 7. Equivalent circuit with dual RC pair

The full ECM contains three parts besides the voltage source (V_{oc}).

The first part is the Ohmic resistance (R_0).

The second part circuit block consists of a parallel equivalent resistance (R_1) and capacitor (C_1), which characterizes the diffusion of Li+ ions across the concentration gradient and the mass transport effects and dynamic voltage performances and the accumulation and dissipation of charge in the electrical double layer.

The third circuits block part accounts for the elements described as the diffusion resistance and diffusion capacitance. It consists of a parallel equivalent resistance (R_2) and capacitor (C_2). And the transient behavior of the cell was captured using three resistors and two capacitors.

The state space formulation in discrete time domain is the following [14]:

$$\begin{cases} SoC(k+1) = SoC(k) - \dfrac{\Delta t}{Q_{nom}} I(k) & (1) \\ V_{CT}(k+1) = e^{-\frac{\Delta t}{\tau_{CT}}} V_{CT}(k) + R_{CT}\left(1 - e^{\frac{\Delta t}{\tau_{CT}}}\right) I(k) & (2) \\ V_{Dif}(k+1) = e^{-\frac{\Delta t}{\tau_{Dif}}} V_{Dif}(k) + R_{Dif}\left(1 - e^{\frac{\Delta t}{\tau_{Dif}}}\right) I(k) & (3) \end{cases}$$

$$V(k) = V_{ocv}(SoC(k)) - V_{CT}(k) - V_{Dif}(k) - R_0 I(k) \qquad (4)$$

Q_{nom} is the battery nominal capacity and Δt is the discrete time step.

The input current I(k) consider as positive during discharging and negative during charging [14].

Thus, the discrete-time non-linear state space battery model can be written into the following state form:

$$\begin{cases} x(k) = A\,x(k) + B\,u(k) \\ y(k) = g(x(k), u(k)) \end{cases}$$

The thermal behavior of the battery can be represented by a thermal equivalent circuit (Electrical-Thermal Analogy) as shown in below figure 8 [23]. Heat generation that occurs inside the battery due to its joule heating effect increases its temperature.

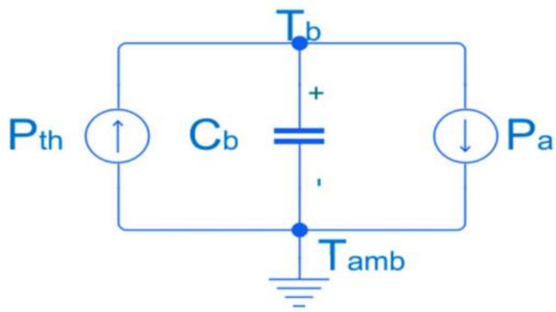


Figure 8. Thermal equivalent circuit

The irreversible heat made by joule effects can be expressed as [23]:

$$P_{th} = R_o(SOC, T_b)I^2(t) \tag{5}$$

The energy balance equation of a battery cell is defined as follows:

$$P_{th} = R_o(SOC, T_b)I^2(t) = m_b C_{p,b}\frac{dT_b}{dt} + P_a(t) \tag{6}$$

Where:

m_b is mass of battery[kg]

$C_{p,b}$ is specific heat capacity of the battery [J/Kg.K]

T_b is uniform temperature inside the battery [K].

P_a is heat transfer rate to the cooling system [W]

P_{th} represents the heat generated due to joules effect. The capacitor represents the thermal mass of the battery storing the energy where C_b=$m_b C_{p,b}$ and P_a represents the heat exchange between the battery and the cooling system [23].

2.2. Matlab/Simulink implementation

The complete battery model including cycle counter, equivalent circuit and observer is presented in Figure 9.

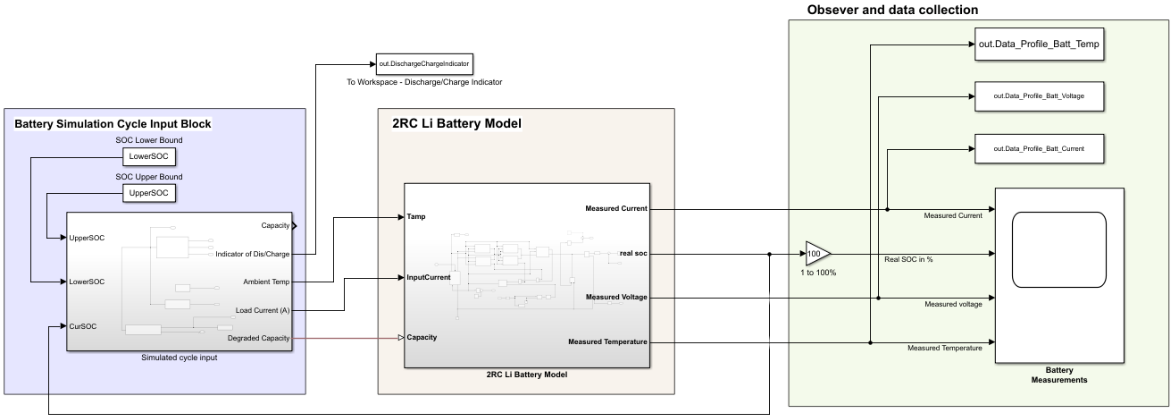


Figure 9. Battery model in Simulink

Based on the previous Dual RC model, to have a more precise model which involves temperature impact, a simple thermal model using joule effect to simulate the heating of battery is added the model.

The RC pair uses the look/up table to give the access of three parameters as Temperature, SOC, and Capacity/Resistance to fulfill the internal characteristic of RC circuit.

The input port $I_{current\ input}$ provided the experimentally measured current.

The input temperature given as environment impact from external side where give a more precise simulated option for the battery performance.

Input Capacity is linked to an externa cycle block where cycling effect can be realized.

The internal resistances include ohmic resistance Ro.

The output port SOC was an output of the EKF algorithm.

The equivalent capacitances which include electrochemical polarization capacitance C_1 and concentration polarization capacitance C_2.

Hence a simulated battery has been realized for mathematical model inside Matlab/Simulink using Simscape, see figure 10.

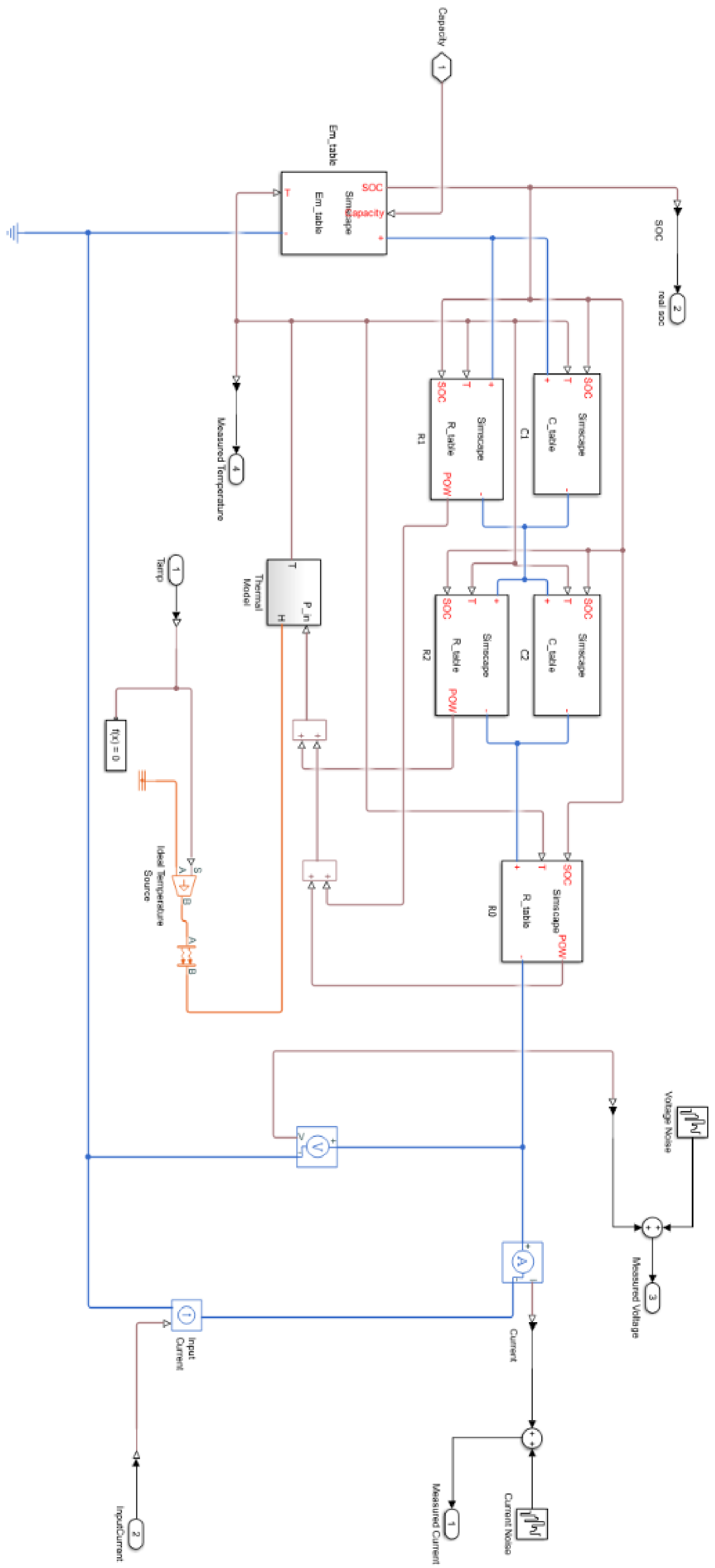


Figure 10. MATLAB implementation using Simscape on dual RC battery model

To enable the battery that can alternate between charging and discharging cycle, the input of battery has been connected to a designed input block Figure 11.

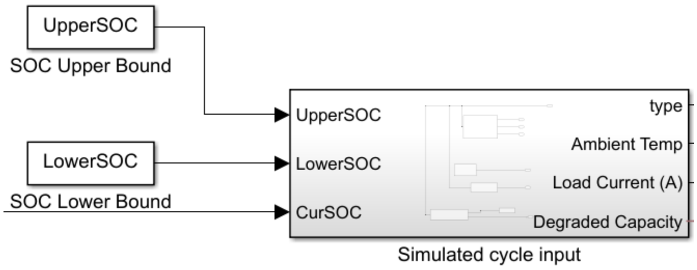


Figure 11. SOC threshold and counting block for battery model

Inside this block a designed charge and discharge cycle can be inserted refer to standard maneuver or customized maneuver, random condition can be also realized using a random input algorithm.

The upper/lower Soc boundary given the access to setup a desired battery working limit, normally from 20% SOC to 100%, can be used for specified setup if necessary.

The capacity of the battery degrades with every discharge-charge cycle, giving as output SOC estimation after aging condition. For analysis which is not related to aging effect can be manually setup as constant.

Here from the full system which also requires the monitoring of State of Health the function is linked to a closed loop which is simulating a degraded condition in theoretical condition.

For experimental use, the data shall be analyzed by the performance of battery via battery marker to have accurate degradation characteristics.

A short preview of a random discharge and charge cycle with related SOC, terminal volatge and temperature variation can be see as below figure 12.

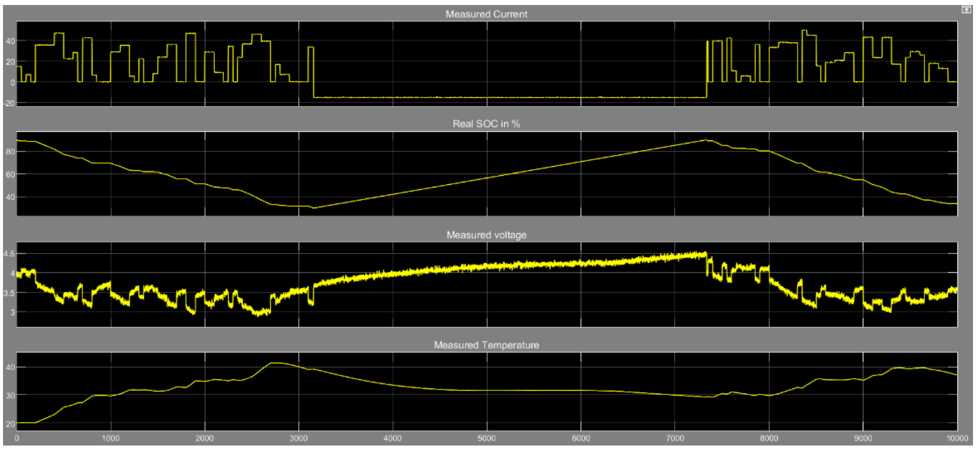


Figure 12. Battery Output Dynamics from Dual RC ECM

2.3. Comparison of modeling consistency with validated model-Battery Model

Using scaled input current from standard load cycle - LA92 to compare with validated battery data from experimental side, the previous built simulation environment has reproduced the similar battery dynamic condition compared to the real battery data from Figure 13. And Figure 14.

Even the during the buildup phase different value of RC characteristics and battery capacity has been used, due to the built in RC characteristics is like Li-ion battery, the dual RC plant can be considered valid for training and study case.

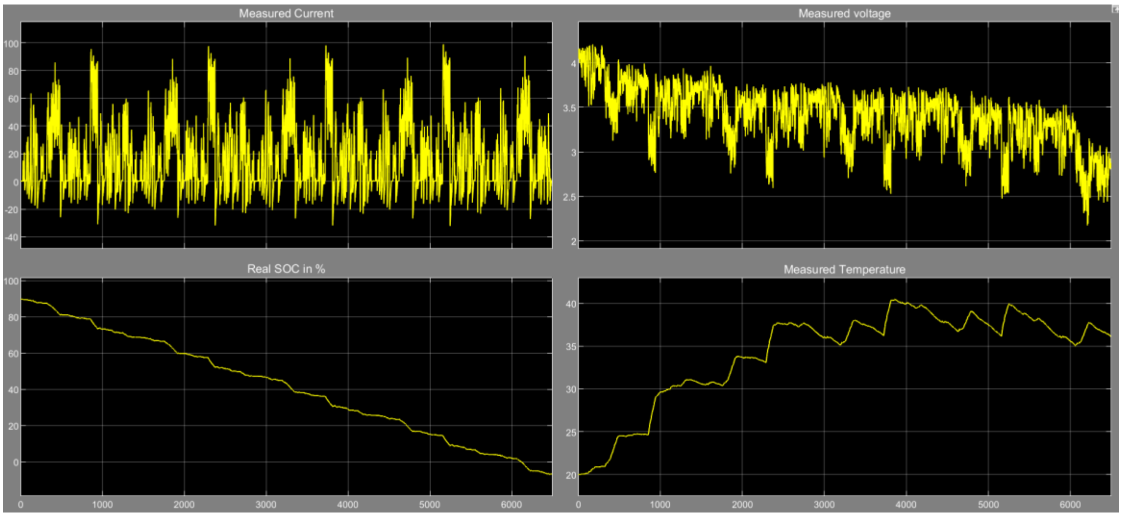


Figure 13. Battery Output Dynamics from Dual RC ECM – Standard Load Cycle LA92

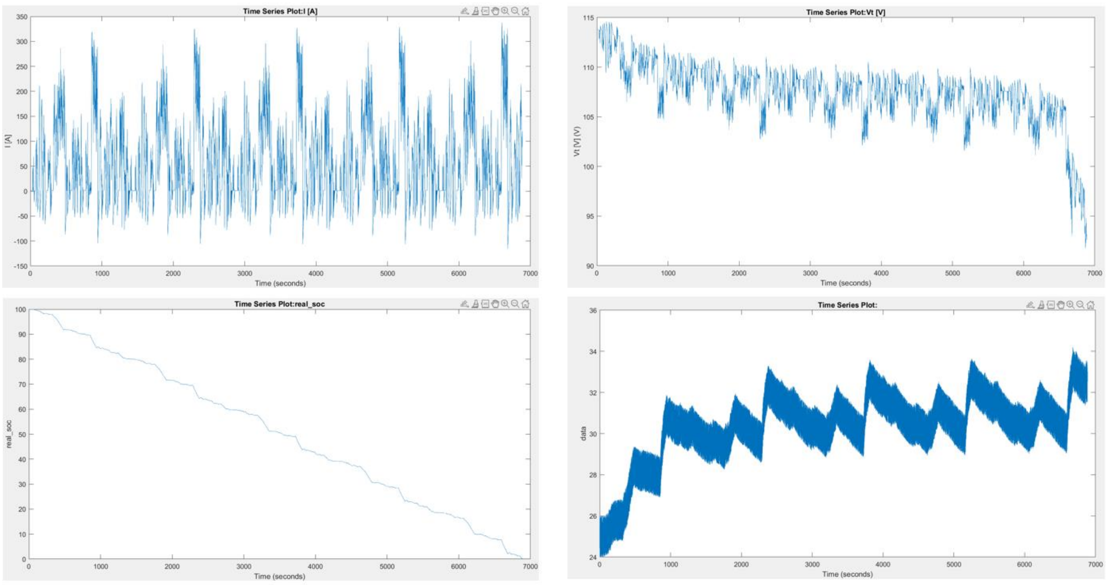


Figure 14. Battery Output Dynamics from Validated Battery – Standard Load Cycle LA92

Limitation using battery model for direct measurement

The previous build battery model using ECM can only represented a similar dynamic characteristic of real battery for its robust behavior. The actual difference and accuracy followed by the decay of battery health is quite non-linear. Which will be presented in chapter 6 when introducing the real battery state nonlinearity.

The internal resistance followed with drop of battery state of health will cause the increase of battery temperature which the joule effect equivalent circuit become no longer a precise estimator inside the battery model. Thus, this will impact the actual voltage drop of the battery

3 Extended Kalman filter

The model-based SOC estimation method is self-adjusted by the difference between the battery's measured voltage and the model's output voltage. This has been done to overcome the error caused due to uncertainty and achieve the purpose of improving the estimation accuracy of the SOC [10]. With this method it needs in-depth research, laboratorial experiments and extended time frame, a complex model and related mathematics equation shall be built to adapt various battery model development.

In particular, the hysteresis voltage does not depend linearly on the current $I_{ocv}(q)$ is also non-linear. Therefore, the original Kalman filter cannot be used here [25]. The extended Kalman filter (EKF) can handle these nonlinear dependencies [26].

The Kalman filter is the optimum state estimator for a linear system. For nonlinear systems a linearization process takes place at each time step to approximate the nonlinear system as a linear time varying (LTV) system [17]. It inherits the ability of the Kalman filter to estimate the best possible values of the inputs containing unmeasured noise.

The principle of the extended Kalman filter for SoC estimation has shown in Figure 15.

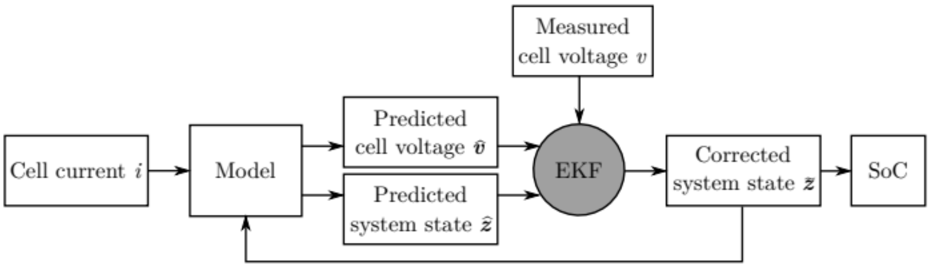


Figure 15. General layout of Extended Kalman filter

3.1 Modeling of Extended Kalman Filter

Following from the previous built ECM battery model, for applying the EKF to SoC estimation, the general system description of the EKF with the battery model and equivalents are identified. The Extended Kalman filter is a method for predicting the future state of a system based on the previous ones and convenient form for online real time processing. It consists of two equations.

The dynamic nonlinear system generally can be described by using the following state space model:

$$x_{k+1} = f(x_k, u_k) + w_k \tag{7}$$

$$y_k = g(x_k, u_k) + v_k \tag{8}$$

The state vector is x(k) = $[q(k)\ \ V_{R1}(k)\ \ V_{R2}(k)\ \ V_{Ro}(k)\ \ \ V_h(k)]^T$

Where x_k is the system state matrix and one of the matrix value represents SoC.

Therefore, x_k captures the system dynamics.

The input of the system is $u_k = [i(k-1)\ \ sgn(i(k-1))\ \ i(k)]^T$ which is a control variable matrix and known or can be measured [27].

The state and measurement equations include A ,B, C and D matrices that can be constituted following previous battery model:

To take k as the time index.

$$x(k+1) = Ax(k) + Bu(k) + w_k \tag{9}$$

$$y(k) = Cx(k) + Du(k) + v_k \tag{10}$$

The second equation is the measurement equation and models the output voltage of the system y_k, in terms of the input, the state vector and the noise in the measurement of the output v_k, which is called measurement noise [27].

Assume that the state transition and measurement equations for a discrete-time nonlinear system have non-additive process and measurement noise terms with zero mean and covariance matrices Q and R, respectively:

$w_k \sim$ N (0,Q_k) processes uncertainty with a covariance matrix Q_k

$v_k \sim$ N (0,R_k) measurement uncertainty with covariance matrix R_k .

After the identification of these equivalents, the matrices needed for the EKF algorithm can be derived, then the EKF matrices A, B and C are obtained, as stated by the following Equations:

$$\mathrm{A}[k] = \left.\frac{\partial f}{\partial z}\right|_{z[k-1],\boldsymbol{u}[k]} = \mathrm{diag}(1,\ e_1,\ e_2,\ e_h,\ 0) \tag{11}$$

Where $e_1 = e^{-\frac{\Delta t}{\tau 1}}$ and $e_2 = e^{-\frac{\Delta t}{\tau 2}}$, $e_h = e^{-\left|\frac{\eta(k-1)i(k-1)\gamma}{Qcell}\right|\Delta t}$,

$\eta[k-1] = 1$ for $i[k-1] \geq 0$ (discharging) while $= \eta$ for $i[k-1] < 0$ (charging)

$$B[k] = \left.\frac{\partial f}{\partial \boldsymbol{u}}\right|_{z[k-1],\boldsymbol{u}[k]} = \begin{pmatrix} -\eta[k-1]\cdot\Delta t & 0 & 0 \\ R_1(1-e_1) & 0 & 0 \\ R_2(1-e_2) & 0 & 0 \\ -\frac{\eta\gamma\Delta t}{Q}(\operatorname{sgn}(i[k-1])\cdot v_h[k-1]+M)\cdot e_h & -M(1-e_h) & 0 \\ 0 & 0 & R_0 \end{pmatrix} \tag{12}$$

$$C[k] = \left.\frac{\partial g}{\partial \boldsymbol{z}}\right|_{\boldsymbol{z}[k],\boldsymbol{u}[k]} = \begin{pmatrix} \frac{\partial v_{oc}}{\partial q} & -1 & -1 & 1 & -1 \end{pmatrix} \tag{13}$$

The measurement noise matrix R is found as the precision of the voltage measurement:

$$R[k] = Cov(y[k]) = {\sigma_v}^2 \tag{14}$$

The determination of the process noise matrix $Q[k]$, which is defined as $Q[k] = Cov(z[k])$ will be tuned in the later implementation.

A summary of a nonlinear EKF algorithm equation is shown in following Table for the prediction and correction steps [16]:

Prediction Step:

$$\begin{aligned} \hat{\theta}^-(k) &= \hat{\theta}(k-1) \\ P_\theta^-(k) &= P_\theta(k-1) + Q_\theta \end{aligned} \tag{15}$$

Correction Step:

$$\begin{aligned} L_\theta(k) &= P_\theta^-(k)C_\theta(k)^T \ (C_\theta(k)P_\theta^-(k)C_\theta(k)^T + R_\theta)^{-1} \\ \hat{\theta}(k) &= \hat{\theta}^-(k) + L_\theta(k)[V_{exp}(k) - g\left(x(k), u(k), \hat{\theta}^-(k)\right)] \\ P_\theta(k) &= (I - L_\theta(k)C_\theta(k))P_\theta^-(k) \end{aligned} \tag{16}$$

In the prediction step, the estimated state $\theta\hat{}$ and its covariance matrix P_θ are projected to the next time step using the dynamic model equation defined for θ in and the noise covariance Q_θ respectively [16]. In the correction step, the parameters vector estimation $\theta\hat{}$ and its covariance P_θ are corrected by using the information from the measurements and the adapted Kalman gain L_θ.

3.2 Implementation & Results

For a well-performing EKF, the tuning and initialization of the filter is critical

The relevant matrices for tuning are the measurement noise R[k] and the process noise Q[k]. For the initialization, the initial state x˜[0] and its error P˜[0] must be set.

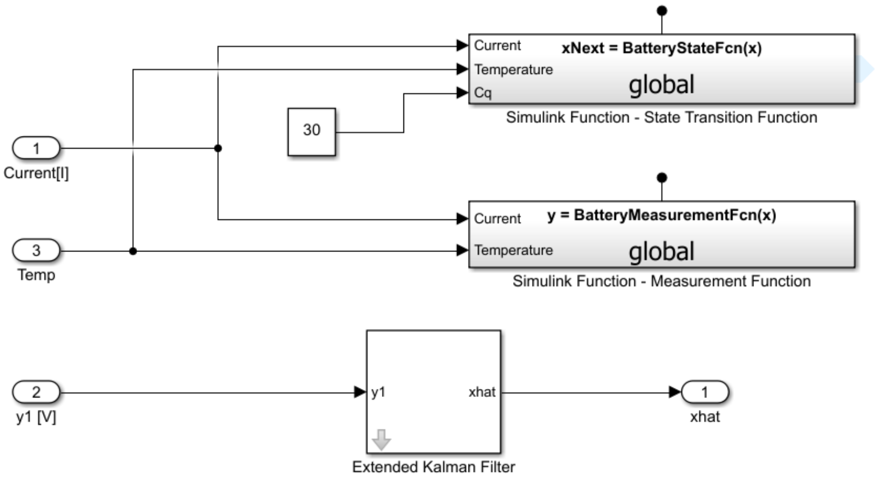


Figure 16. State function and measurement built from Simulink

During the build-up phase inside Simulink, figure 16, the discretized state transition equation is implemented as function named [batteryStateFcn]. The function input |x| is the state vector, and the function output [xNext] is the state vector at the next step, calculated using the discretized state transition equations.

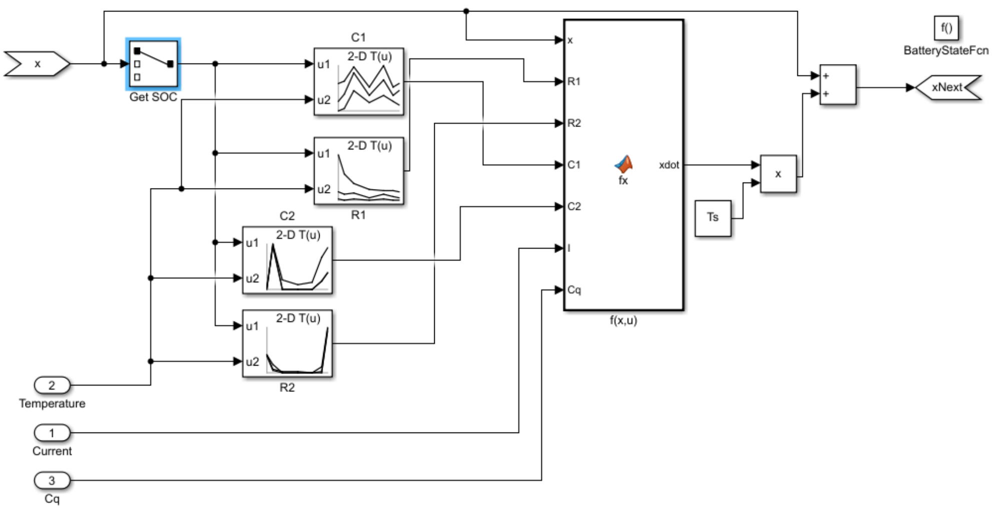


Figure 17. Detailed state function block of Simulink Model

In the function, it is specified with the signal dimensions and data type of [x] and [xNext]. Additional inputs to [batteryStateFcn] are the temperature, estimated capacity, and current. Similarly, the measurement function is also implemented in the Simulink function named [batteryMeasurementFcn].

After the setup of the state function for monitoring the battery plant, inside the Extended Kalman filter block, the estimator equations are summarized as the figure 17 [18].

With the support of MATLAB block function, the prediction and correction steps has been integrated inside the Simulink from figure 18.

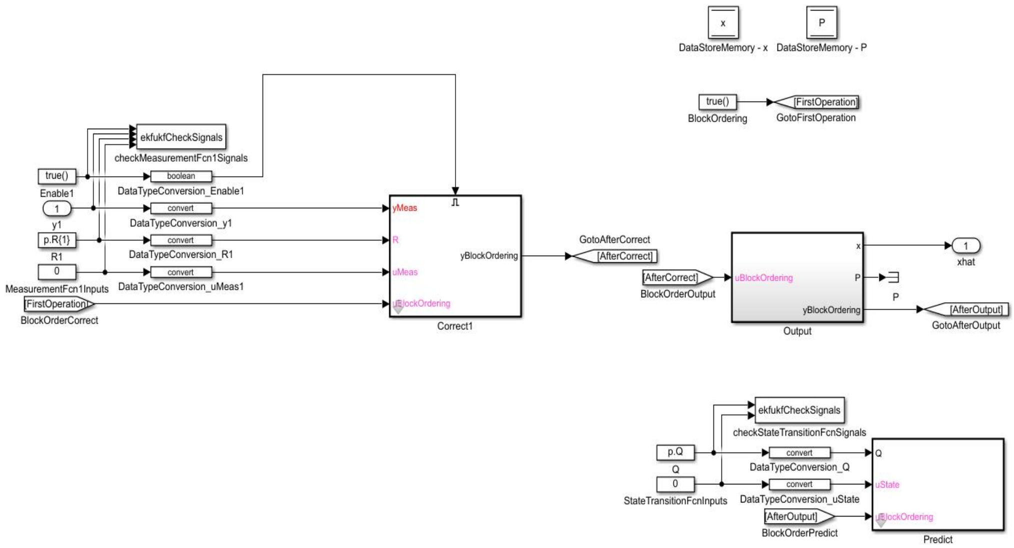


Figure 18. Correction block and prediction block of Simulink Model

The tuned result can be seen as below that for the estimated SOC from extended Kalman filter for a known battery model and known initial condition can be very precise. This indicates that to obtain a good SoC estimation with model-based algorithms, the accuracy of the state space model is a crucial point to get good compliance, result as can be seen from Figure 19 and Figure 20.

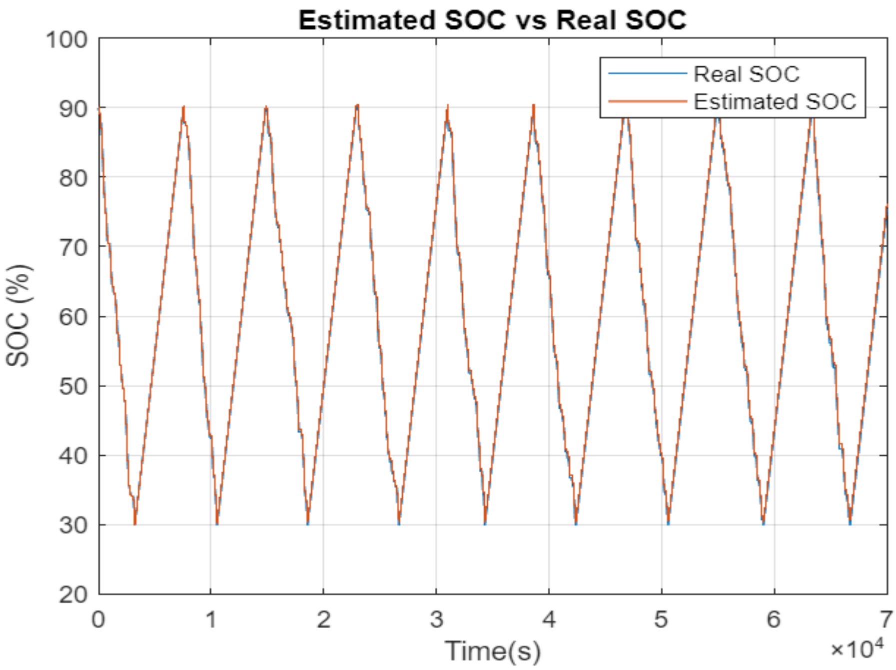


Figure 19. Tracking performance on SOC estimation of EKF

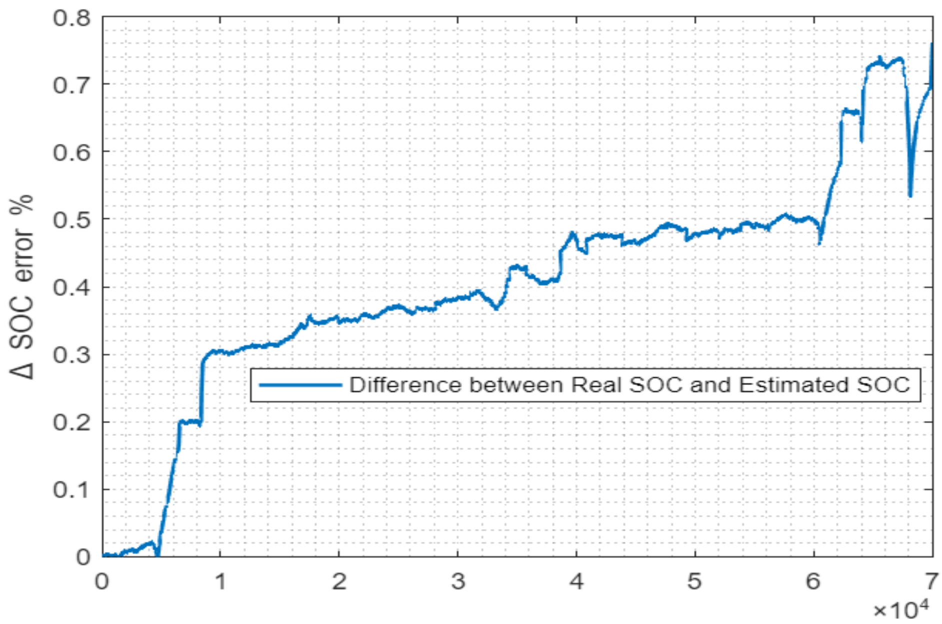


Figure 20. Tracking Error on SOC estimation of EKF

4 Neural Network Technique

Neural Network has robust algorithm to perform under different battery dynamics, dynamic loads, and different temperatures. The main benefits of using Neural Network are that they do not need the mathematical model and they can handle any nonlinear and complex system.

Some challenges exist for this method in determining the most influential features, activation function, number of neurons in hidden layer and learning rate. Many NN based methods have been investigated for SOC estimation of the lithium-ion battery.

4.1. Introduction of Neural Network principal

The neural network combines multiple nonlinear processing layers, using simple elements operating in parallel and inspired by biological nervous systems. It consists of an input layer, several hidden layers, and an output layer [21]. The layers are interconnected via nodes, or neurons, with each hidden layer using the output of the previous layer as its input.

The following systematic learning workflow has been taken as reference to setup the learning method [20]:

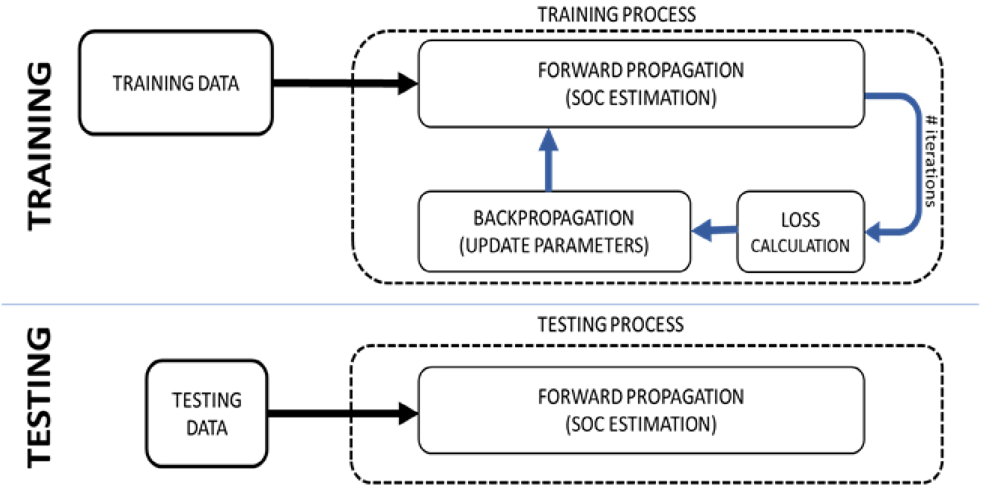
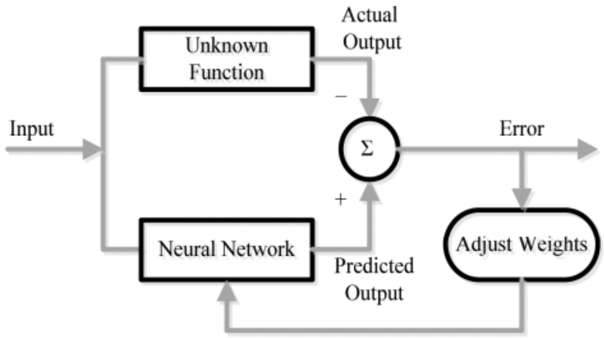


Figure 21. Systematic learning workflow of neural network technique

By refereeing to this method to our study object, it can be understood that to take the feature of output characteristic from a Battery as previous implemented for Model-base method, and use it as the reference input, to let the machine learning as our approach for a certain training data, using robust algorithm to perform under different battery dynamics, dynamic loads, and different temperatures.



The neurons are interconnected through weight functions as shown in figure 22, each loop of learning phase forming probability-weighted associations between the "input" and "result," which are stored within the data structure of the net itself, using Backpropagation to adjust the connection weights to compensate for each error found during learning.

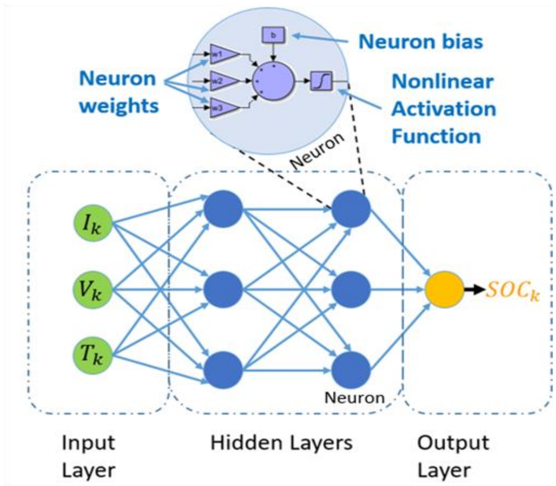


Figure 22. Basic structure of Neural Network for SOC estimation

The error amount is effectively divided among the connections. Technically, backprop calculates the gradient (the derivative) of the cost function associated with a given state with respect to the weights. The weight updates can be done via stochastic gradient descent or other methods [35].

4.2. Description of Neural Network type

From this study, we have directly used the dual RC battery model plant as an assumed battery source for the following test. And the following network type is implemented to compare the difference and its accuracy:

a) Time delay non-linear input output neural network (TDNN)
b) Time series NARX network (NARX)
c) Multi-layer forward neural network (MLFNN)

Time Delay Neural Network

The Nonlinear Input-Output Network predict values of $y(t)$ from previous values of $x(t)$, but without knowledge of previous values of $y(t)$ [20]. This input/output model can be written as follows:

$$y(t) = f(x(t-1), \ldots, x(t-d)) \text{ [20]}$$

as a default model, it will be implemented as first approach to test the method, better or more complex mode will be implemented later for improve the performance using neural network technique.

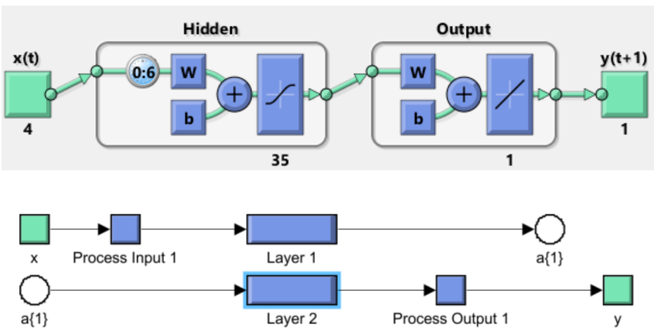


Figure 23. General layout of Time Delay Neural Network

In this architecture, one can notice that the observations of the time series are given as inputs, and the first step is the memory. The network must memorize the input values for a sequence of last inputs, or with a different lag than the one from the original series, one with a lower granularity [29].

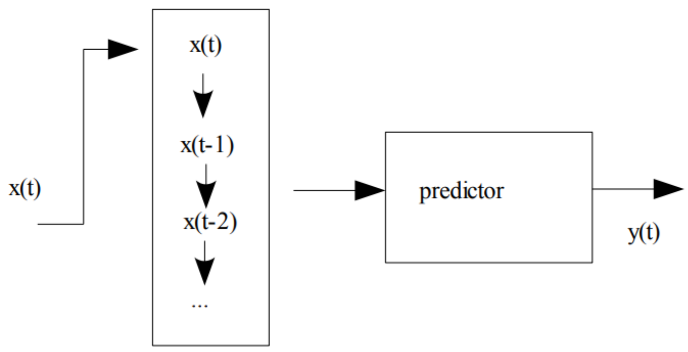


Figure 24. A tapped delay line memory system

Next, the system needs a predictor, that can base itself on both inputs and predicted values , but also on training data : correct outputs. In this case we denote x(t) as the input at time t, and y(t) the output. The memory usually has recurrent connections, while the predictor is a feedforward usual network [30].

Tapped delay line memory is formed of n buffers containing most recent inputs. Which represents the time delay function from this neural network mode, every oldest input is replaced by a new one, and each input takes part in the learning process per turn. This model is the base for autoregressive methods.

For estimating the SOC, the input time series x(t) consists of the battery terminal voltage(V) battery temperature(T) and current(I), where the output or target is the SOC.

Time series NARX network

The Nonlinear Auto-Regressive with eXogenous inputs model(NARX) is a kind of dynamic recurrent neural network defined by the following:

$$y(t)=f(x(t),\ldots,x(t-a),y(t-1),\ldots,y(t-b),d(t-1),\ldots,d(t-b))$$ [20]

It introduces the concept of time series, which makes the NARX model have good dynamic characteristics and high anti-interference ability. The basic network structure of the NARX neural network is the same as that of the ANN [20]. It uses feedback connections, enabling lateral or backward information flow within the network. This makes the NARX neural network have good dynamic characteristics and strong anti-interference ability.

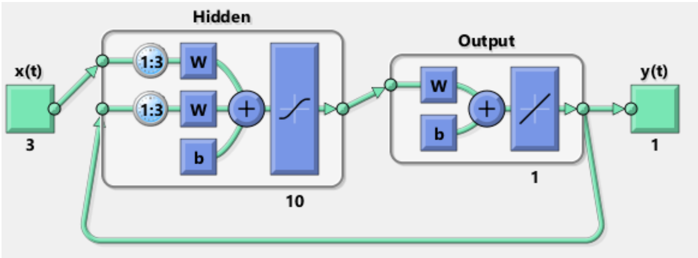


Figure 25. General layout of NARX Recurrent Neural Network

NARX model can then be built on a recurrent neural network, trained by BPTT (backpropagation through time) algorithm or simple BP (back propagation) if the feedback is removed [29]. In this thesis only closed loop recurrent neural network trained with BPTT has been implemented for having comparison with other network layouts.

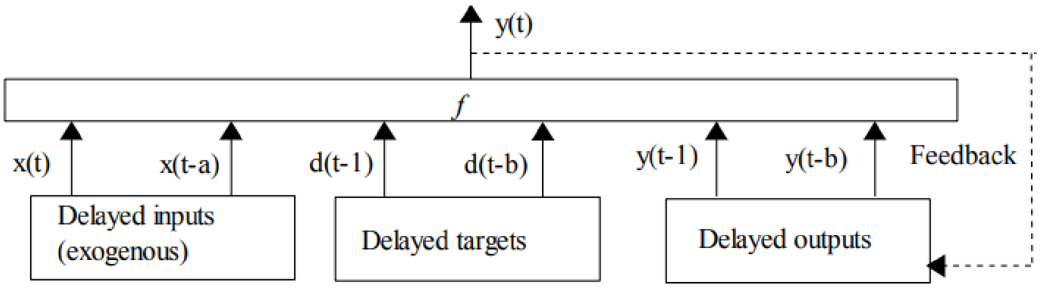


Figure 26. Theoretical NARX model

From Figure 26 NARX can use the regressors with different lags[31] and this time they no longer have the same lag as the series but the input regressor is a τ separated selection of inputs from the original time series. This allows the network to cover more space to determine long term dependencies, but with bigger granularity.

Customized multi-layer feed forward neural network (FNN)

The Feed Forward networks are the simplest neural networks because the information moves in only one direction forward. they are used for any kind of input to output mapping and with sufficient neurons in the hidden layer they can fit any target curve. A three-layer feedforward BPNN model is used in this research for the estimation of SOC. The first layer is the input layers to characterize the inputs variables, the second layer consists of one or more hidden layers and the third layer is the output layer to characterize the output variables.

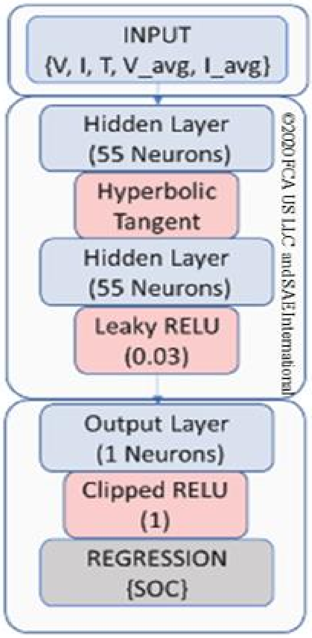


Figure 27. Reference structure of MLFNN network

Several considerations has been made as assumption for the improvement of this comparison network inside the studies

Multiple hidden layers for networks are created using the different activation function

As with the single-layered ANN, the choice of activation function for the output layer will depend on the task that we would like the network to perform (i.e. categorization or regression). However, in multi-layered NN, it is generally desirable for the hidden units to have nonlinear activation functions (e.g. logistic sigmoid or tanh)[21]. This is because multiple layers of linear computations can be equally formulated as a single layer of linear computations. Thus, using linear activations for the hidden layers doesn't buy us much. However, using linear activations for the output unit activation function (in conjunction with nonlinear activations for the hidden units) allows the network to perform nonlinear regression.

Increased number of neurons

If an inadequate number of neurons are used, the network will be unable to model complex data, and the resulting fit will be poor. If too many neurons are used, the training time may become excessively long, and, worse, the network may overfit the data. When overfitting occurs, the network will begin to model random noise in the data. The result is that the model fits the training data extremely well, but it generalizes poorly to new, unseen data. Validation must be used to test for this.

Change training option

From the previous 2 network layout, the network training is performed using Levenberg-Marquardt (LM) algorithm because it has good training speed and maintains very good accuracy [32]. From the customized the FNN, Training option has been set for Adam (adaptive moment estimation) optimizer, including learning rate information, L_2 regularization factor, and mini-batch size.

4.3 Modeling & Network training using MATLAB tool

Initializing the training of Time delay neural network(TDNN) and NARX via MATLAB using command 'nnstart' can provide a quick access for this study using default time delay network. By selecting the prepared dataset from the previous built simulation for input and output, the program will start the learning phase. While the customized multi-layer feedforward net is required with Matlab code structure to specify in detail on network layout and network features.

Modeling of neural network can be down using the following process:

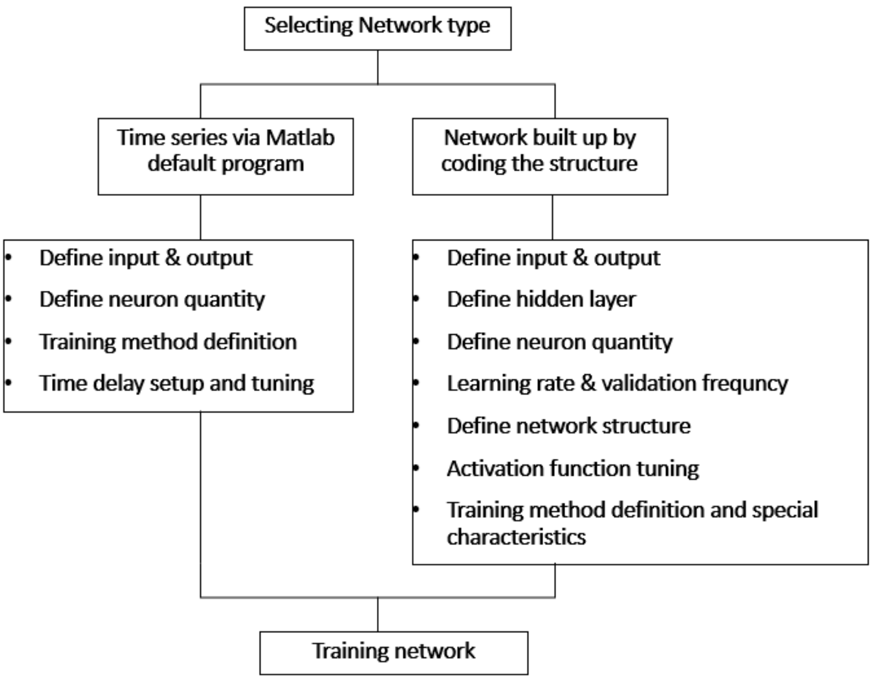


Figure 28. General modeling process

Data preparation for Network Training

The following output training data has been extracted from the previous build Simulink model and prepare into a matrix format for using as input & output data for the Network training inputs. Voltage, Current, SoC, Temperature obtained from Simulink model has been indicated as following:

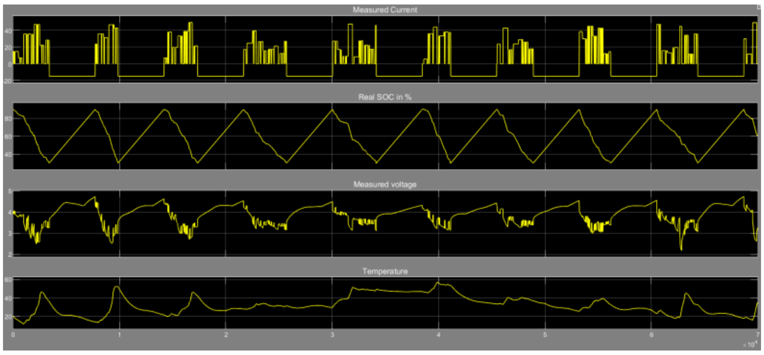


Figure 29. Data sampling from simulation

The data extracted via simulation into workspace and rearranged into array form for adapting the MATLAB Neural Network tool. Here the training data has been extracted from a random charge current profile with varied environment temperature where the environment temperature is firstly ascending the descend.

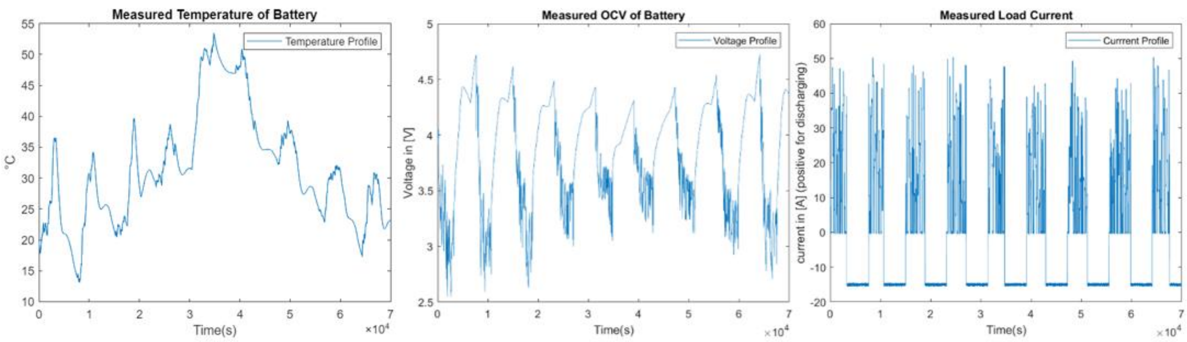


Figure 30. Network training input

Targe Y means the SOC from the battery plant to be used as learning output.

The final data group is converted into an array formed dataset.

```
Input_Voltage = 1×70000
      3.9514    3.9514    3.9514    3.9514    3.9512    3.9507    3.9503 ...

Input_Current = 1×70000
     14.7277   14.7277   14.7277   14.7277   14.7277   14.7277   14.7873 ...

Input_Temperature = 1×70000
     20.0000   19.9999   19.9997   19.9993   19.9983   19.9935   19.9897 ...

Target_Y = 1×70000
      0.9000    0.8999    0.8997    0.8996    0.8994 ...
```

Figure 31. Training data sets

Neural Network Training

The training access is identical to previous TDNN method, the difference is that NARX has it own feedback feature for a close loop structural, where time delay is not really impact the final learning accuracy. So here the basic adjustment of neuron layer and neuron quantity is enough to provide a good training.

During the training process the program will indicate different features that can be tracking in real time during the training. For example, the MATLAB program will provide the time response output as figure 32. for training result reference, where the upper plot is indicating the trace of trained network and lower plot is give the real time tracking error.

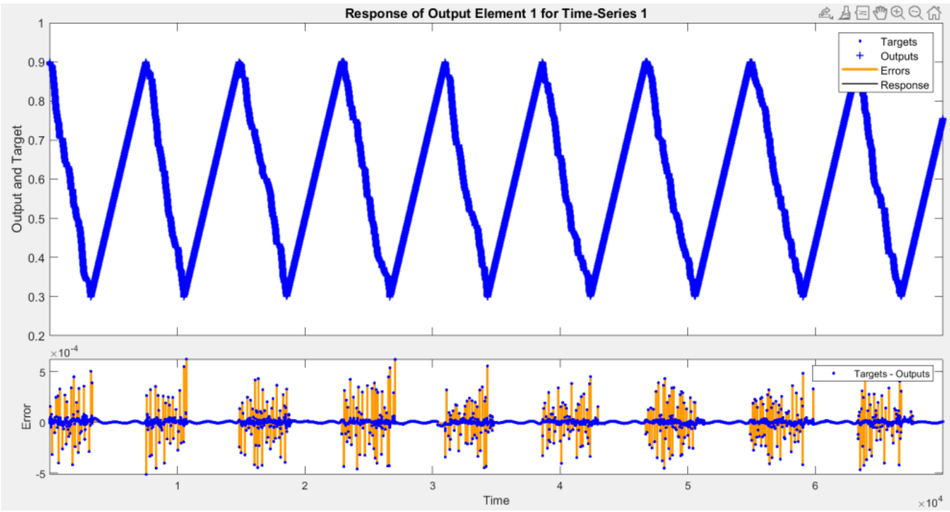


Figure 32. Time Response output from the Network Training

When using coded structural, by selecting inside Performance Factor option with command Plots = " training-process". The program will update the training progress with iteration information and related performance tracking back to the user.

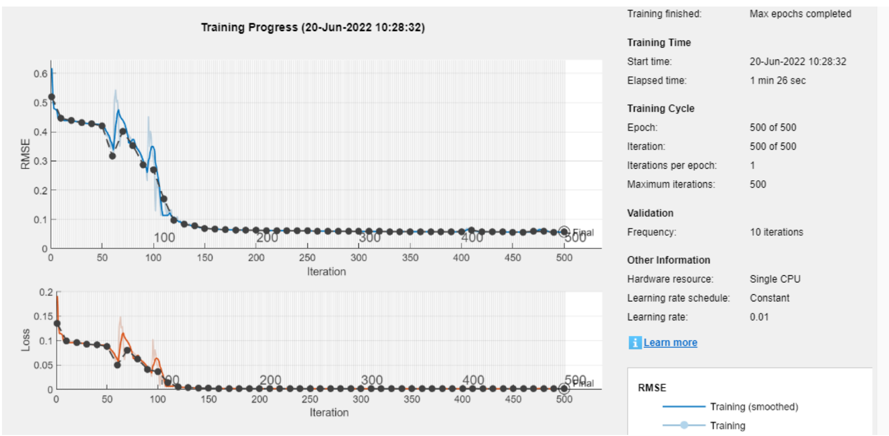


Figure 33. Training progress from the Network Training

The regression coefficient (R) is a good indicator for evaluating the SOC estimation performance. It demonstrates that the value of regression coefficient, and the regression coefficient results are in close agreement to unity which validates the accuracy of the model.

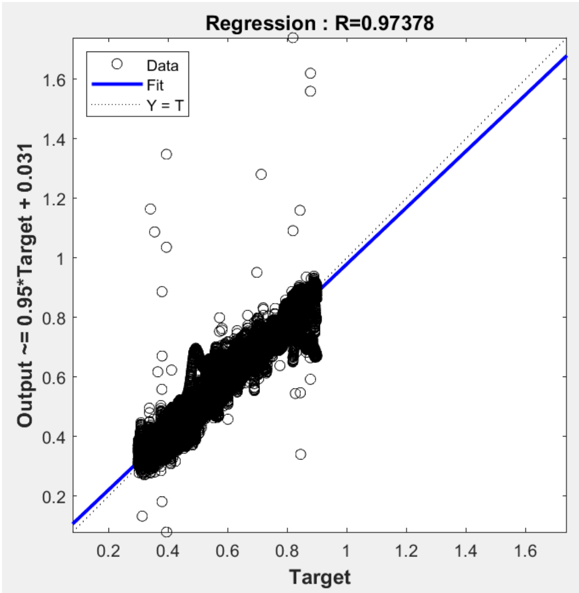


Figure 34. Regression indicator and validation of MSE

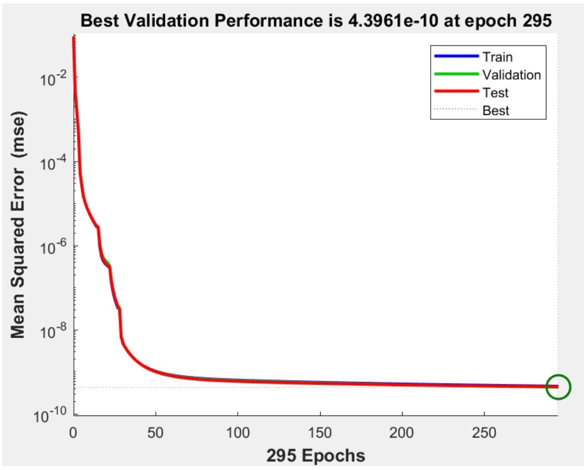


Figure 35. Training performance indicator

Simulink integration

After the network has been training, the validation using other testing data or real simulation implementation can be exported via MATLAB export option or save the trained net into .mat format. From the machine learning toolbox, it has been given an option to insert .mat trained network into Simulink environment.

The following reference of figure 36. has indicated the implementation of trained network inside previous built battery model for running real time simulation.

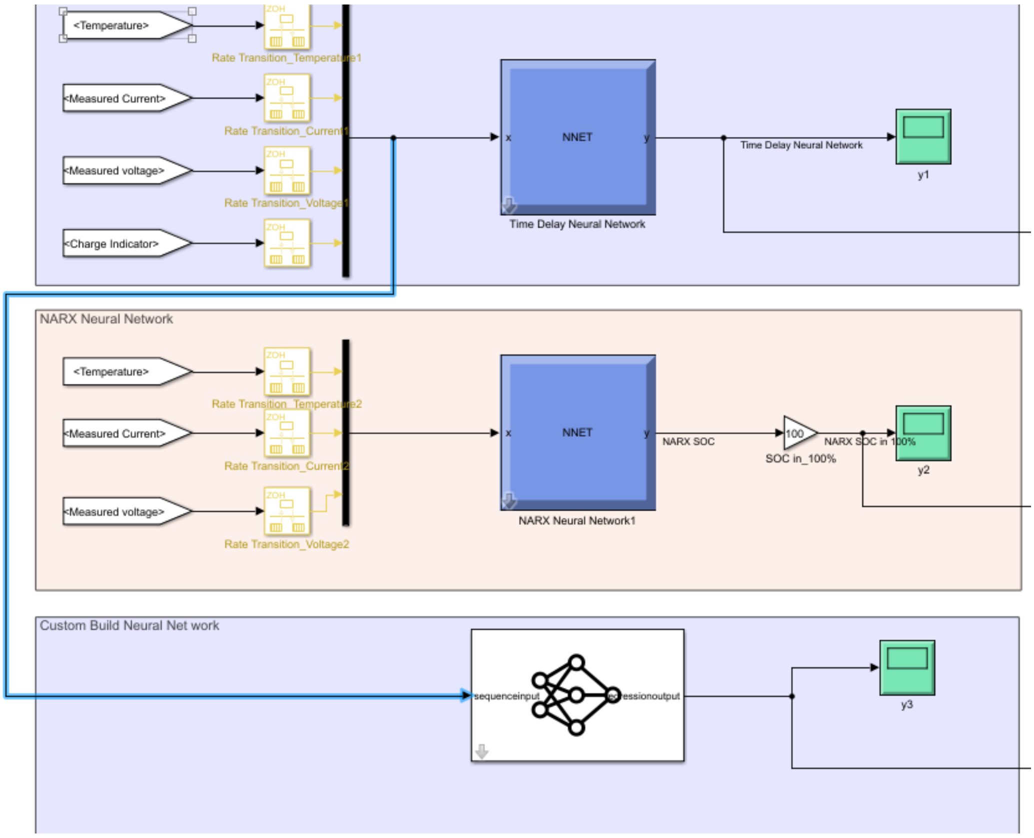


Figure 36. Trained Network implemented inside Simulink

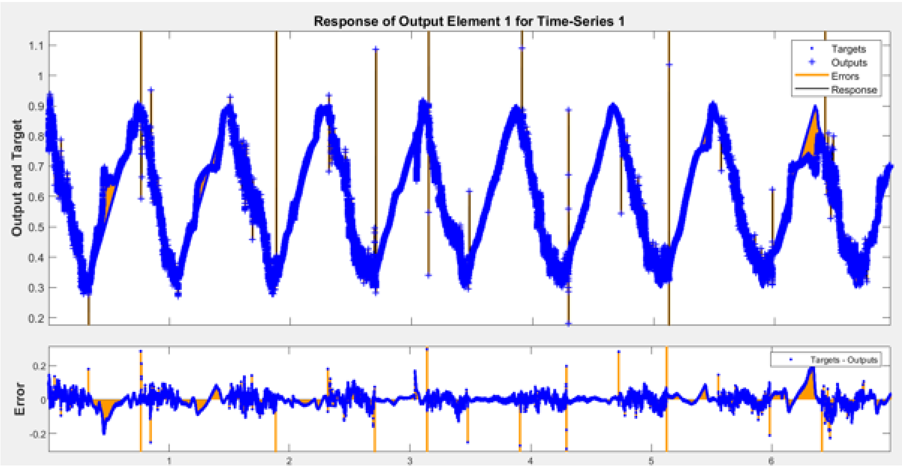
5 Simulation Result

5.1 Result review

From the 2RC battery model using random input current cycle all 3 types of neural network have been trained using same data sets.

From figure 37. It can be observed that both for TDNN and NARX training result presents a generally good tracking performance during discharge phase where for TDNN at low SOC condition the error tend to increase. Following accumulative charging and discharging phase overshoot error appears when changing from charge phase to discharge phase.

- Time delay non-linear input output neural network



- Time series NARX network

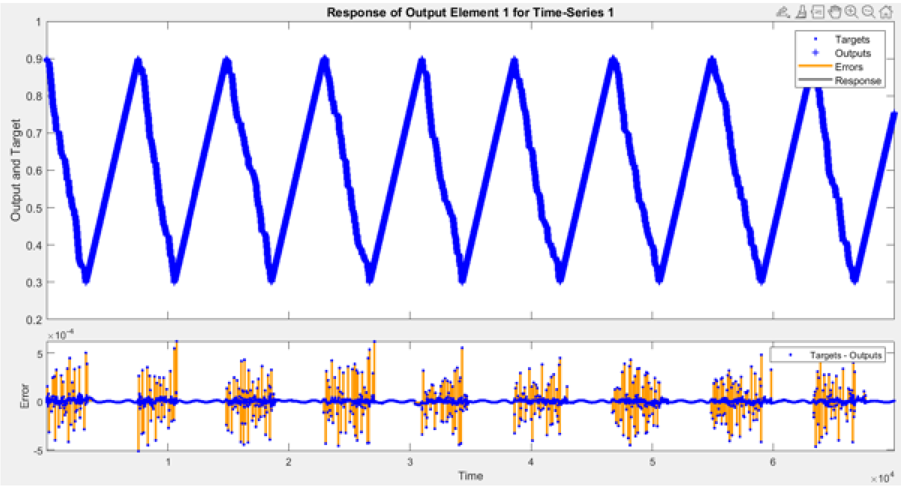


Figure 37. TDNN & NARX training result

The NARX net due to have its own recurrent feature, the trained result indicated a complete learned result with almost no error from the target. Comparing the between Time series network with the multi-layer feedforward network, figure 38. Under same input training data sets, the performance of FNN has obtained very similar error level to the TDNN result.

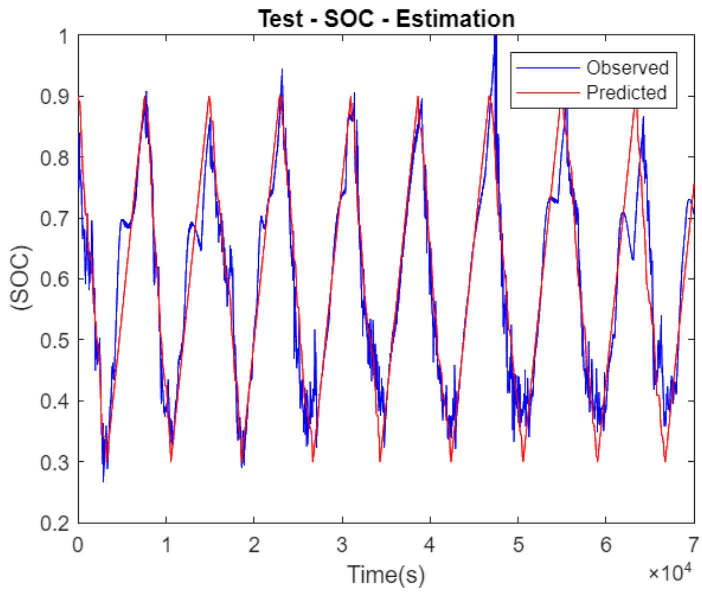


Figure 38. SOC estimation using customized FNN

The MSE[1] indicates around 7% error from the multi-layer forward neural network here for the cyclic charge simulation, but for the single discharge performance the MAE is down to less than 5%, this has led to the consideration of further improvements on building the network and its training process.

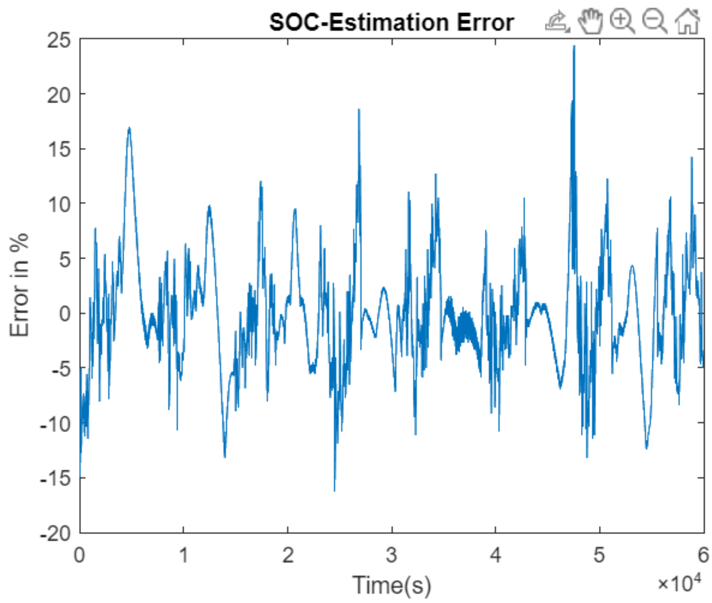


Figure 39. FNN Error tracing during SOC estimation

By adding additional input feature as normalized voltage and normalized input, into multi-layer feed forward training input.

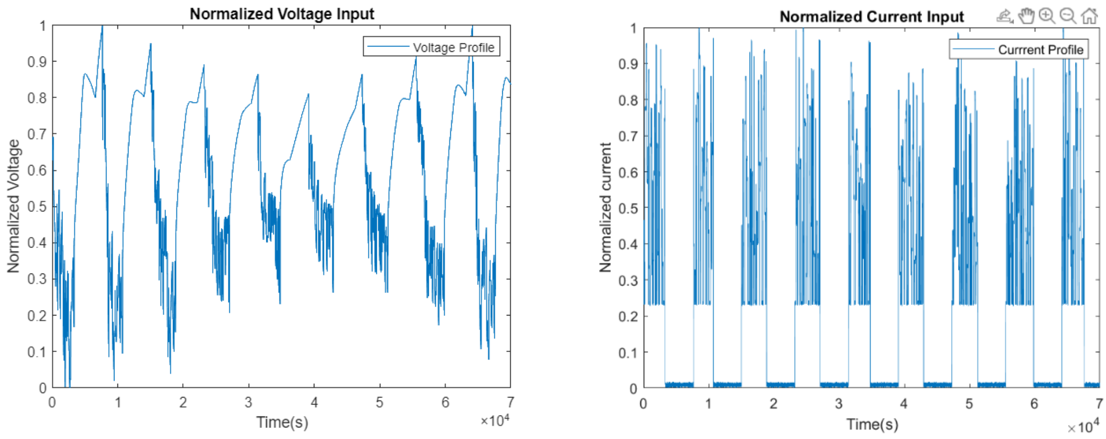


Figure 40. Additional input added for FNN

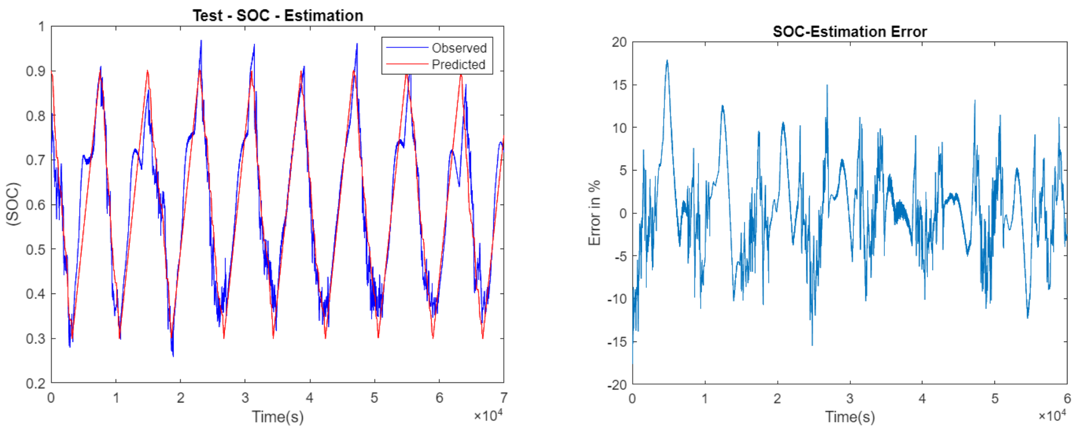


Figure 41. Result improvement using additional inputs

To compare the Error with original model, the over estimation has indicated a better tracking performance close to the Kalman filter method, and MAE drop for cyclic simulation to around 5.7%, the single discharge cycle has also narrow down the error range given around 4%.
From this point the actual application for using neural network method can be concluded to do trials on the experimental test using test data from the Lithium Battery.

5.2 Improvements for FNN SOC estimation result

Based the result obtained from figure above the following improvement direction has been settled for further trial, due to the well performed time series result, the following improvement has been implemented only on the customized FNN.

- Increase hidden layers
- Change Activation function
- Increase hidden neurons
- More data

Considering the computational time that networks spend in training with various layers and neurons, either adding new layers or neurons is not efficient. For example, a 4-layer with 14 neurons in each layer network needs at least 25 minutes for a run to predict response from one dataset and it is more than 1 hour in total to measure the performance of this network. An ideal way to determine the number of layers and neurons is both considering the accuracy and the computational time.

	Improvement	**Learning time**	**Overall tracking performance**
1	Add additional hidden layers with hyperbolic activation function	Increase to 15min for entire simulation	improve tracking performance
2	Increase hidden neurons to higher quantity from 50 to 100 with step 10	Increase with neuron quantity	only slightly tracking performance improved, overfitting could happen when neurons size increases
3	Adding another 3 data sets from stored simulation for network training	Training time acceptable	most simple approach to provide improvements on NN training
4	Adding 3rd layer, increase neurons to 55, taking 3 data for training	20min training period for large data training	for cyclic simulation average absolute error drop around 2.7%.

The final improvement(4) will be carried out for the next phase experimental data validation

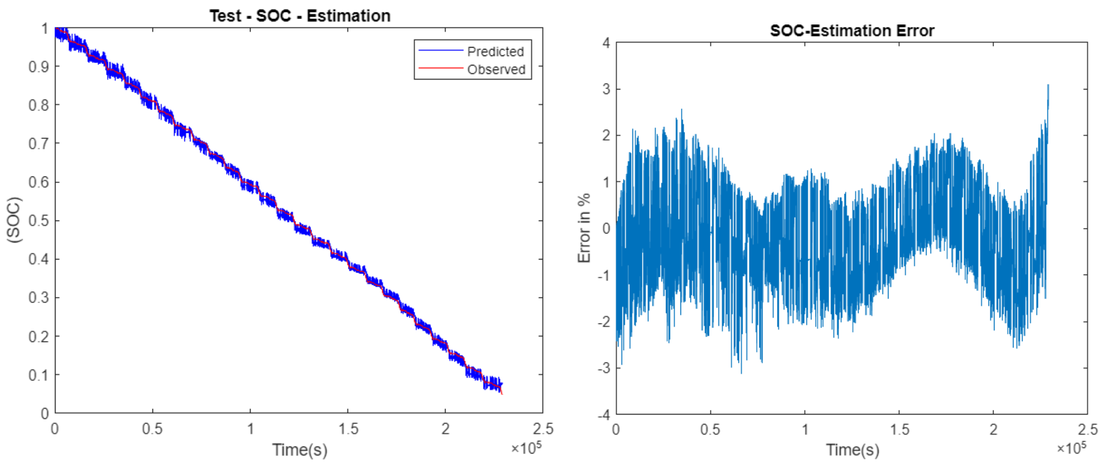


Figure 42. Result of a single discharge estimation using configuration (4)

5.3 State of Health Estimation using NARX

In reality the performance of batteries decreases over time and with use, described as a change in the battery's State of Health (SoH)[21], from the observation of an 18650 cylindrical rechargeable cell a typical decay of battery can be seen on figure 43 :

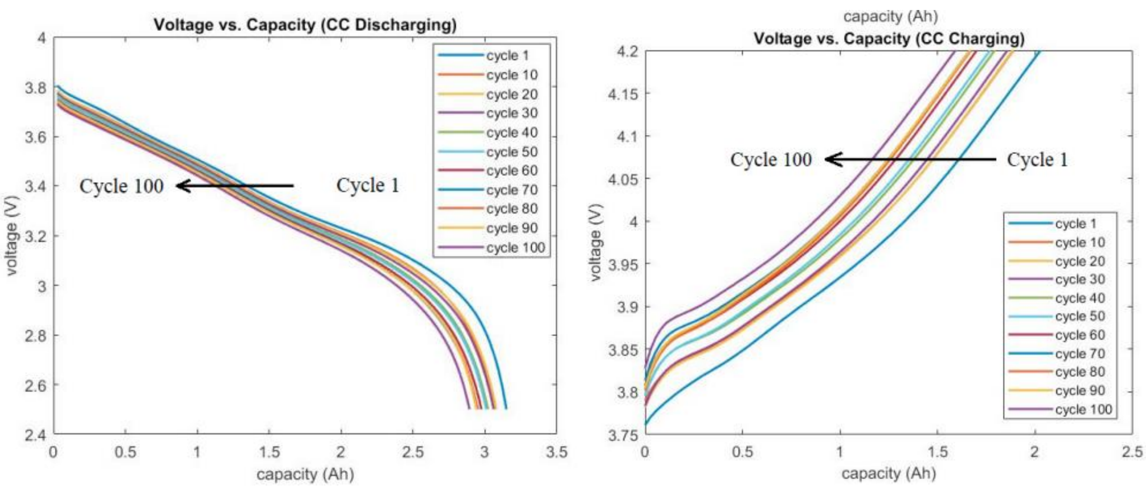


Figure 43. Battery Decay with cycling discharge

With the above variation, the capacity monitoring can be the approach to identify the status. Following the previous model built for SOC from Simulink enviornment, a new kalman filter has been introduced for obseving the simulated decay of health state.

This function has been realized by the cyclic counter and an estimation of cyclic health drop, which inside the simulation enviornment can be setup via actual experimental data or by assumption for validate other algorithme.

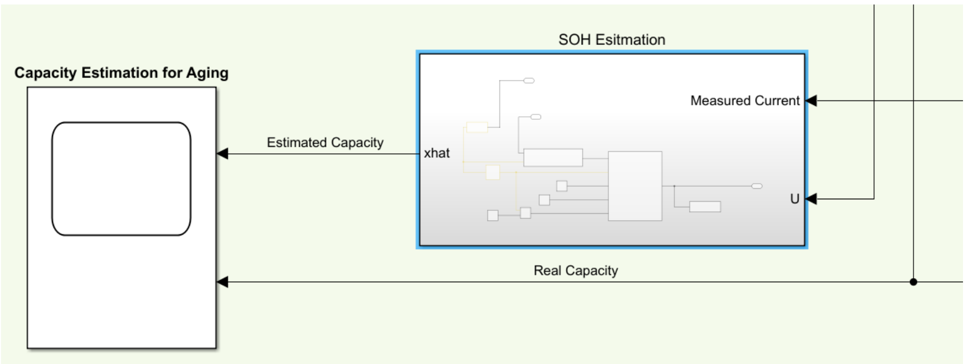


Figure 44. Simulink Model for SOH estimation

The estimation here from the example result below figure 45, indicate the tracking delay of the obseved result due to the filter setup. This can be tuned when real decay of SOH has been inserted. As presented before the simulink enviornment is based on an assumed battery for study use, so there the fine tuning on SoH from previous simulink mode has made less significance.

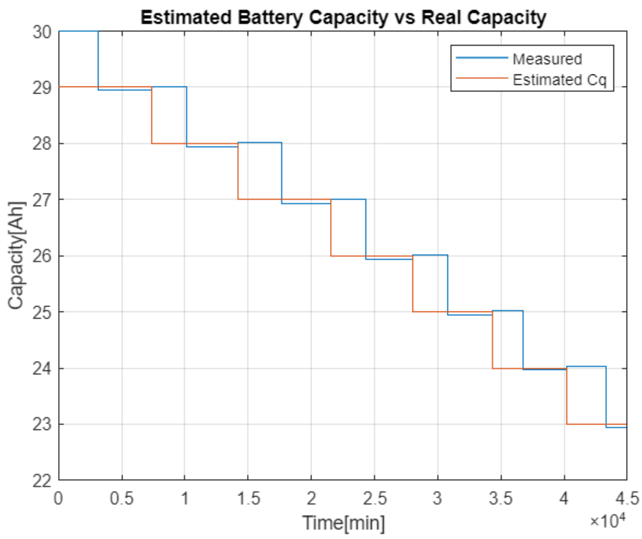


Figure 45. Simulated result from ideal assumption

However the neural network approach is quite suitable when learning from a known battery. Here a NARX type has been choosen for giving initial battery SoH condition of 100%

The method using Voltage, Current and Temperature can be taking into same training by adding or switching the target data from SOC to SOH with cyclic training data input. The training reuslt can be seen from Figure 47.

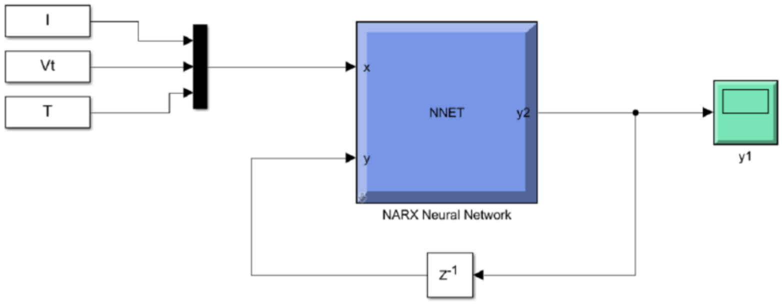


Figure 46. Neural Network learning for SOH drop

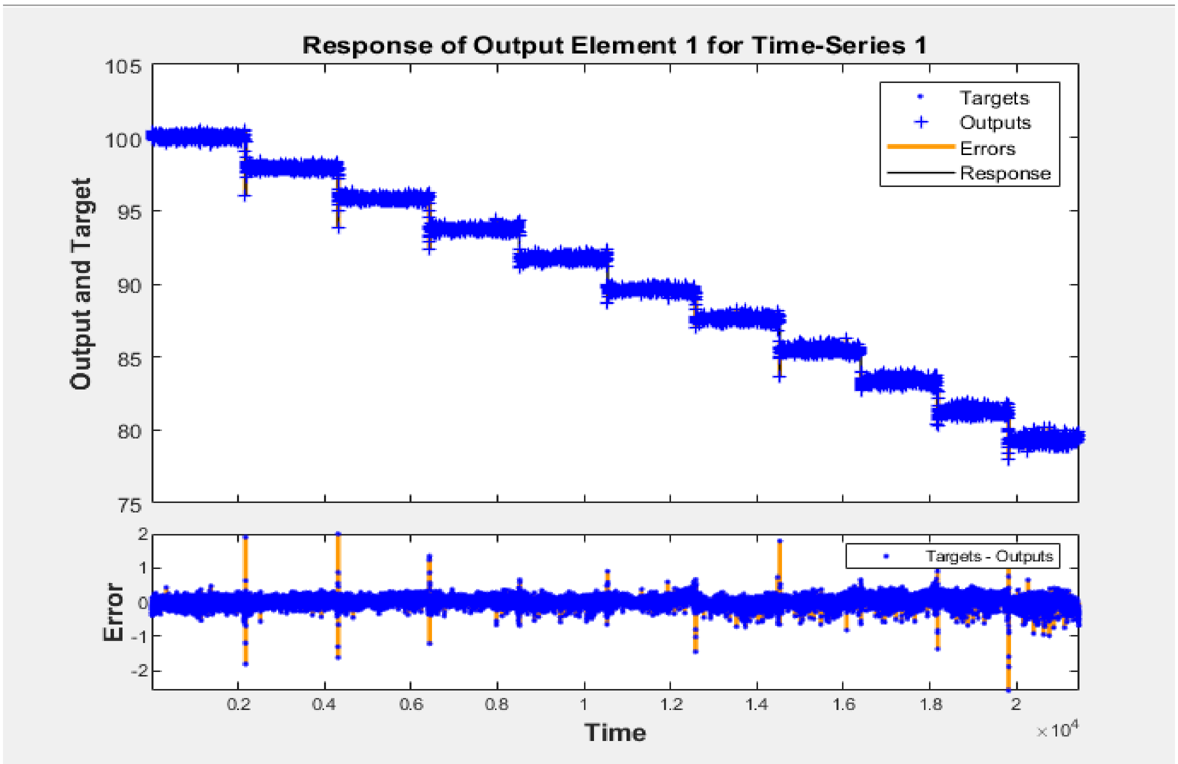


Figure 47. Training Result of SOH tracking

5.4 Validation with actual Li-Battery data

To a known Battery with its data sheet provided from the Battery supplier, the validation pre-condition has been defined as following:

- Battery data sheet available (Cell type: Samsung SDI 94Ah)
- Valid for an entire charge and discharge cycle follow standard profile – for Network training
- Valid for Short Period Check-Test during BMS calibration /BMS on vehicle end-of-line/ single battery quality check

To solve the first issue regarding **Initial State SOC of an Unknown Battery Status**

The following strategy has been proposed:

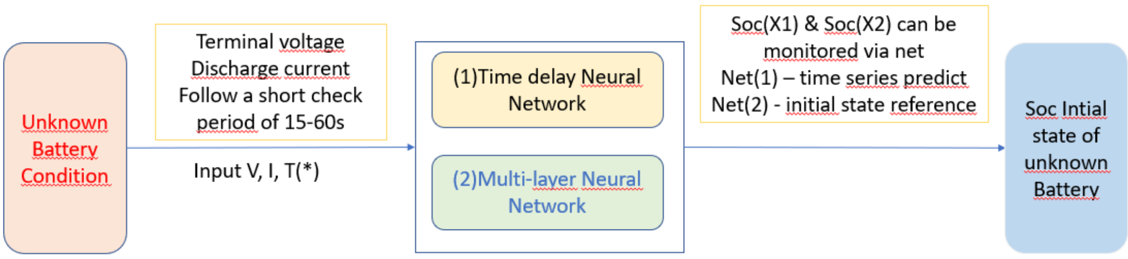


Figure 48. Experimental Validation for defining initial status

T* → temperature can be also isolated from Net, since trained network follows T(0)=25°C, but in real case T(X1) can be controlled or random, in this case this will lead to a self-generated error (e.g. T(x1)=25°C, Soc(x1)=80%, this is not trained by net and will lead to error increasement)

Time delay Neural Network - Study Result & validation Result

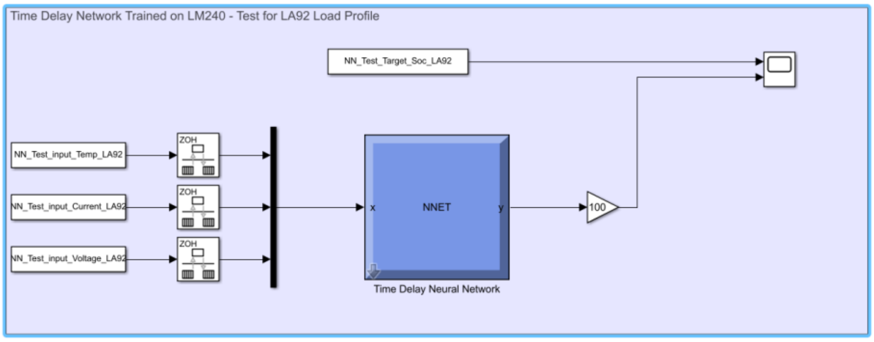


Figure 49. Modeling for TDNN training on experimental data

The preparation flow including a well-trained Time delay neural network from the standard load profile data LM240 which represents the study phase.

Then we take another load profile LA92 tested on the same battery to compare the validation result of the trained net, where can be seen from figure 50, the validation of Trained network presents a very good conformity with almost zero error between the trained range 10-100% of SOC. Where when data input gets in a untrained range errors appears, as it indicated from figure 51 at final stage when SOC drop from 10% close to 0, the error appears. This validates that within a trained range, for the same battery

Network study based on standard maneuver of load cycle LM240

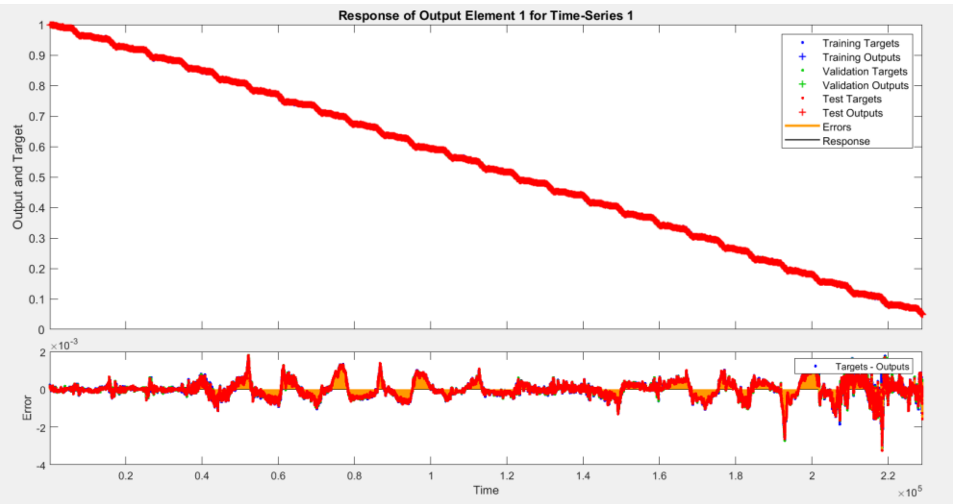


Figure 50. TDNN Training result for experimental data

Trained Network test based on standard maneuver of load cycle on LA92

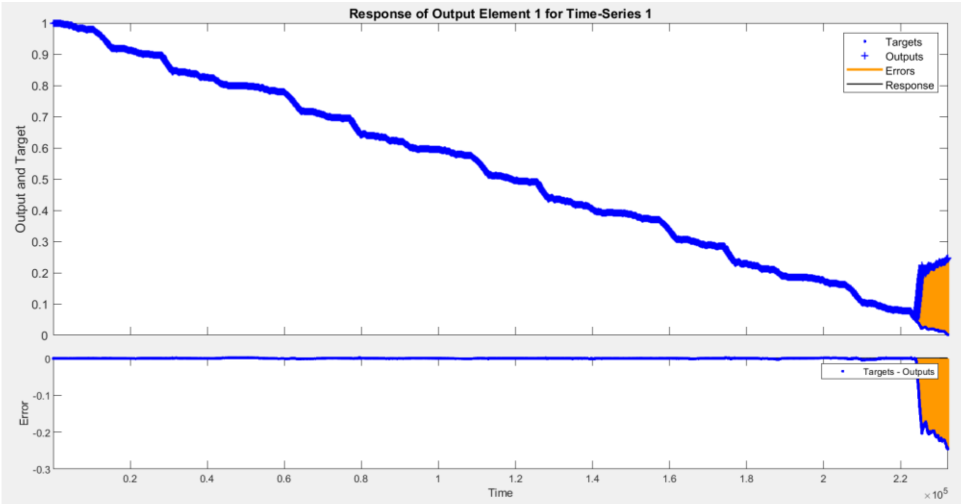


Figure 51. Validate battery performance using trained Net for untrained input cycle

Time delay Neural Network – Real time simulation on Initial time delay [Simulink]

During the simulation using trained network inside Simulink environment, it has been found that under time series simulation the initial delay will trigger a high over estimation zone until the input reaches the trained setup.

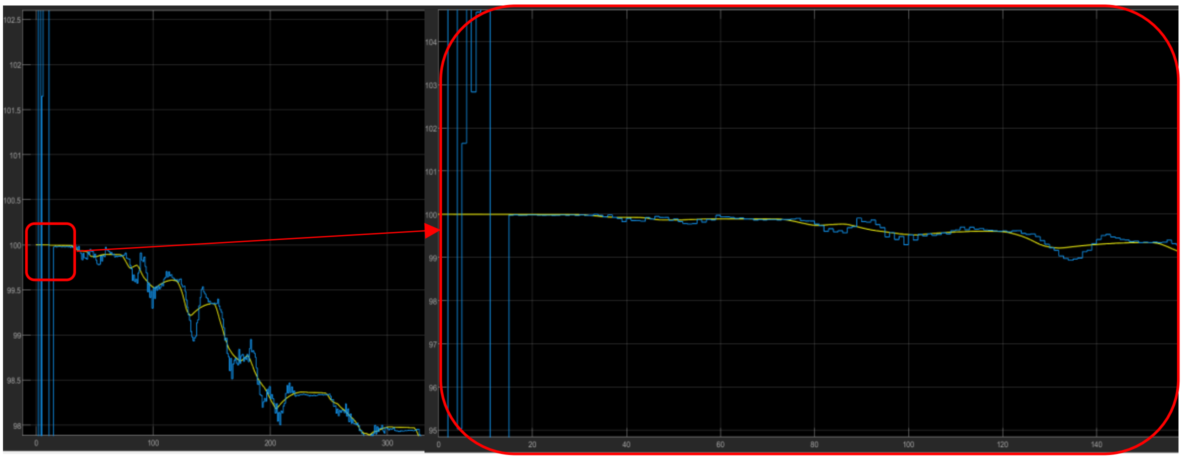


Figure 52. Drawback using NARX network

This is due to the input delay structure where has been assigned during network training. The difference from given dataset for training and real time estimation bring the difference for input calculation.

To eliminate the initial time delay SOC estimation error on Real time measurement, the 2nd Auxiliary Neural network can be implemented in Parallel for compensate and initial loss and initial definition.

As per discovered below, due to the time delay network feature, the estimated data at initial phase will have a high fluctuation. So to avoid this kind of initial condition the idea of using secondary network with pre-trained feedforward network can be good choice for solve the initial inaccuracy of TDNN.

Battery initial state comparison validation

The attached validation scheme with the general layout in Simulink environment can be referred as below

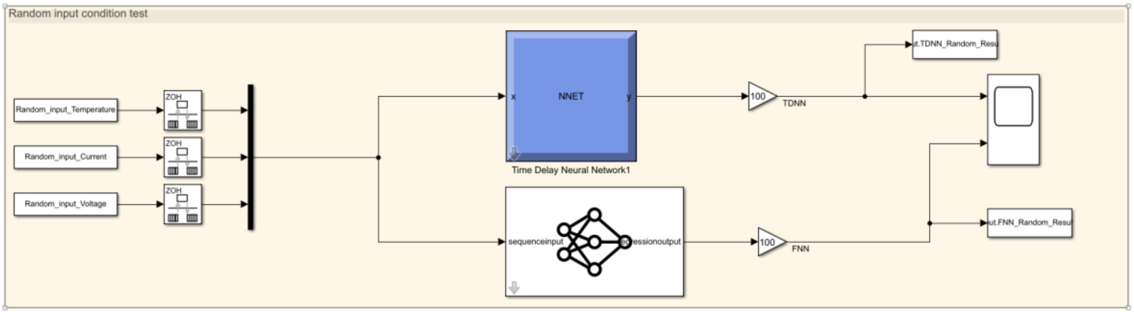


Figure 53. Validation model for initial state defining

The multi-layer neural network recalled from the last improvement chapter has been introduce here, and trained with the load profile of LM240, with a trial of random initial tracking using LA92 load profile. Since the pure forward prediction, this network presents it advantage where a precise estimation of SOC condition will be obtained with acceptable error range.

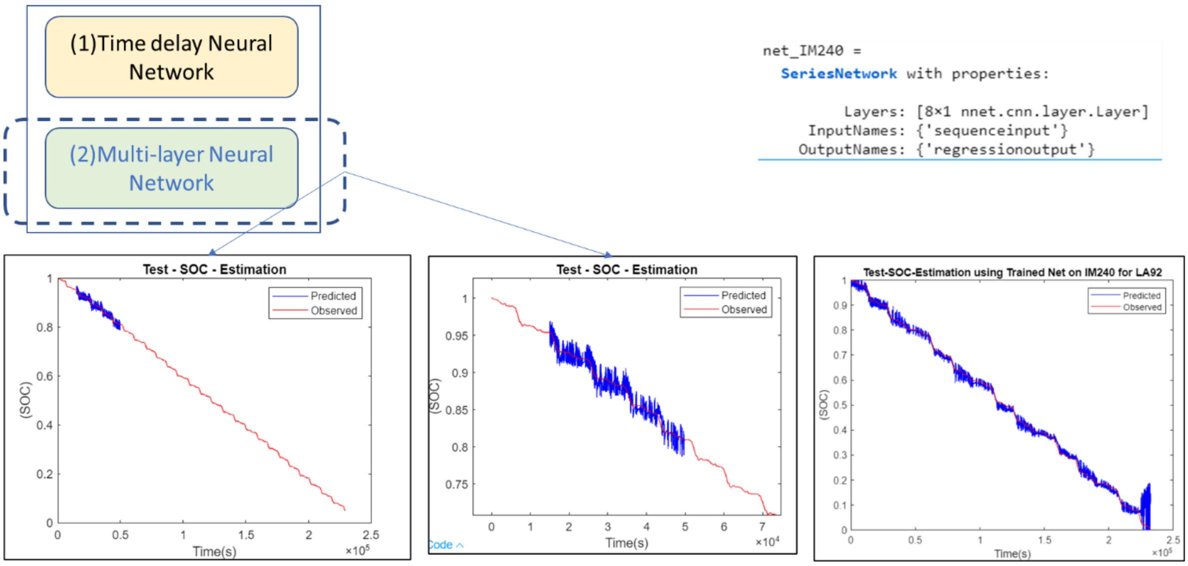


Figure 54. Validation result for initial status tracing using FNN

Original data to a smoothed output for determine the initial SoC, then passing to Time delay Network for further measurement

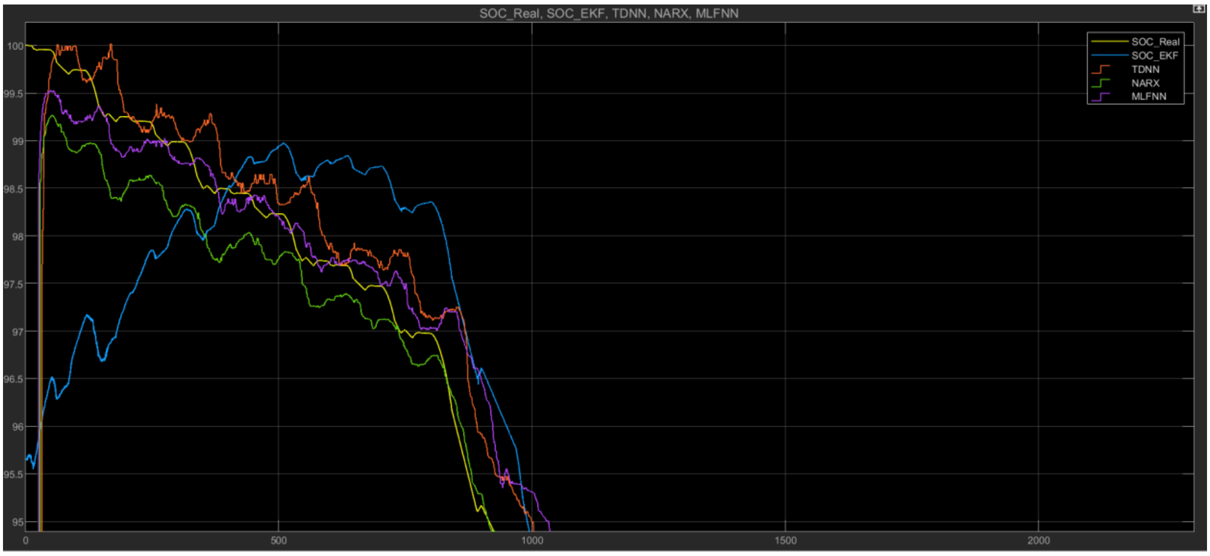


Figure 55. Initial status estimation precision between Neural Network and EKF

The bias between FNN net result to Target can be improved during multi-data training, once validated the net with referred target battery the net can be used for model/program setup. Combining both strategies, a select method or a Main/reference strategy can be defined using TDNN as main net, take FNN for reference data boundary.

5.5 Test result of SOC estimation including SOH effect

To further study the behavior of the neural network, from above verification to real application, using the battery data from the real application with load profile of a standard vehicle drive cycle, the following test has been carried out:

Neural network trained with data target set of 10 discharge cycle on WLTP driving cycle

- ❖ **8 discharge cycle WLTP- SOH 80%-100%-80%-90%-100%-90%**
- ❖ **1 discharge cycle of LA92 (SOH100)**
- ❖ **1 discharge cycle of IM240 (SOH100)**

From figure 56 and 57 we can notice that followed with the drop of SOH to a known battery, it has been discovered the variation of battery dynamics brings the change into its input level.

Especially from the temperature side, due to the increase of internal resistance, the battery input to the net has brought the deviated input pattern, which makes a under trained network less accurate. Followed by the assumption the further training to the network method has been carried on a more completed cycle dataset, which involves different boundary condition where battery data has been sampled under 80 to 100% SOH with different input current load

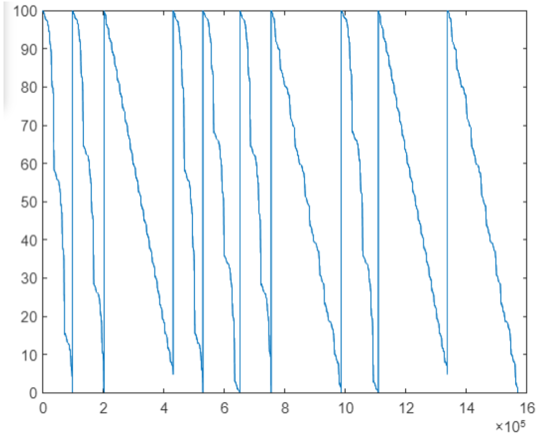


Figure 56. Input SOC Target with 10 Cycle data

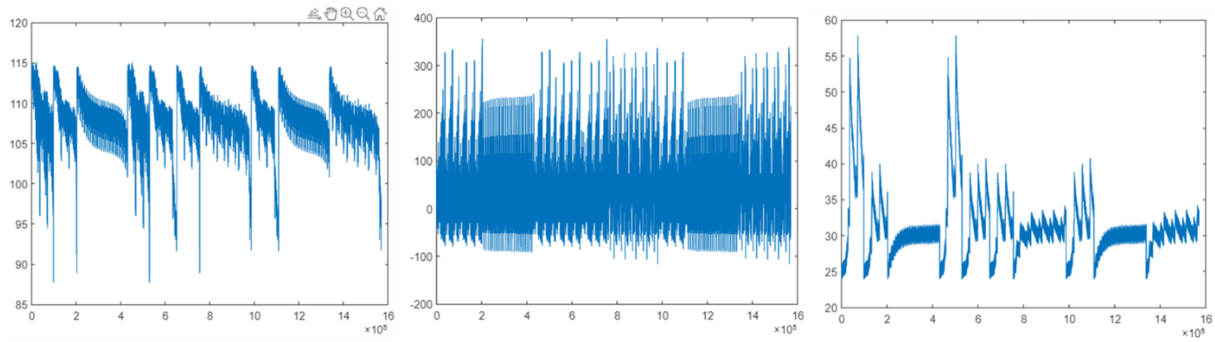


Figure 57. Input training data of Current, Voltage and temperature

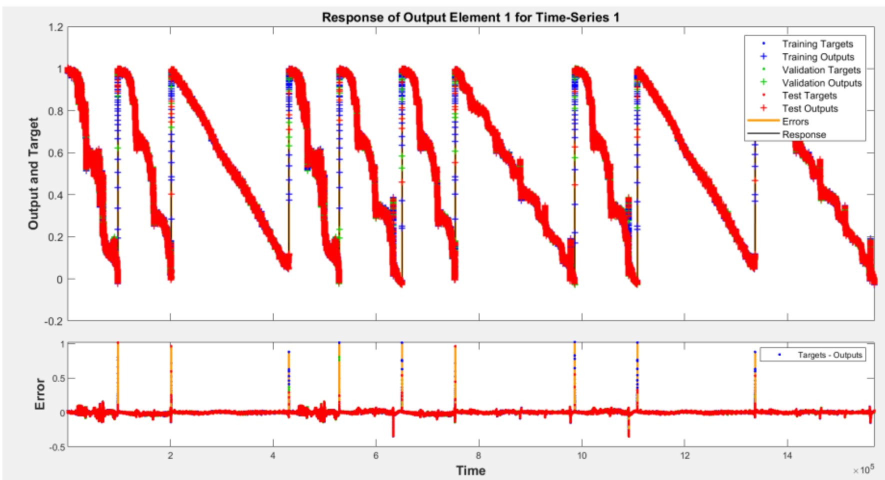


Figure 58. Training result / NARX with 10 Cycle Data

With training result of 0.003-0.004 Mean Square Error(MSE), the NARX net can be considered with successful trained condition, the training time has been increased due to the datasets and increased complexity for the close loop net.

```
trainPerformance = 3.3963e-04
valPerformance = 3.2984e-04
testPerformance = 3.4522e-04
```

The NARX net which has been trained with a good accuracy on its target. For having the boundary dynamic performance inside the range from 80% to 100% SOH

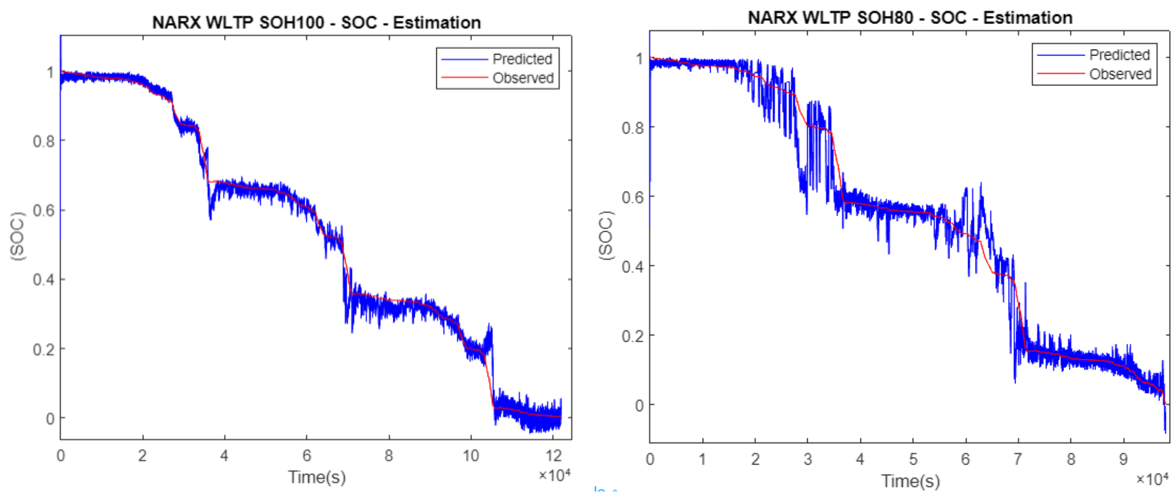


Figure 59. Result comparison between SOH100 & SOH80 for a single discharge

From Figure 59 we can notice that the previous trained network is not able to maintain the track when battery dynamics has been changed due to it decay of health. Therefore, to maintain the Neural network method accurate, a complete data training and full study has become the key to this approach.

This test has identified for the drawback on using neural network, which the more complete the data is used for training the more accurate it can be. Where if more datasets can be learned from well settled Network layout, for a new development battery, the more confident level can be obtained using neural network method.

Updating the previous learned network and cyclic learning schedule can be considered as continues learning method inserted in between the battery development for gathering training competence. And it is easy to be implemented using the normal data gathering as the main input is measured via Battery management system.

6 Experimental Result

6.1 Comparison between EKF and Neural Network Technique

From single loop battery characteristic trained TDNN the accuracy is quite compatibly to EKF with RMSE 0.72 on TDNN and 0.93 on NARX, regarding the multi loop trained NARX Net with RMSE of 1.26, the net has presented a certain confidence level to go on for actual battery test

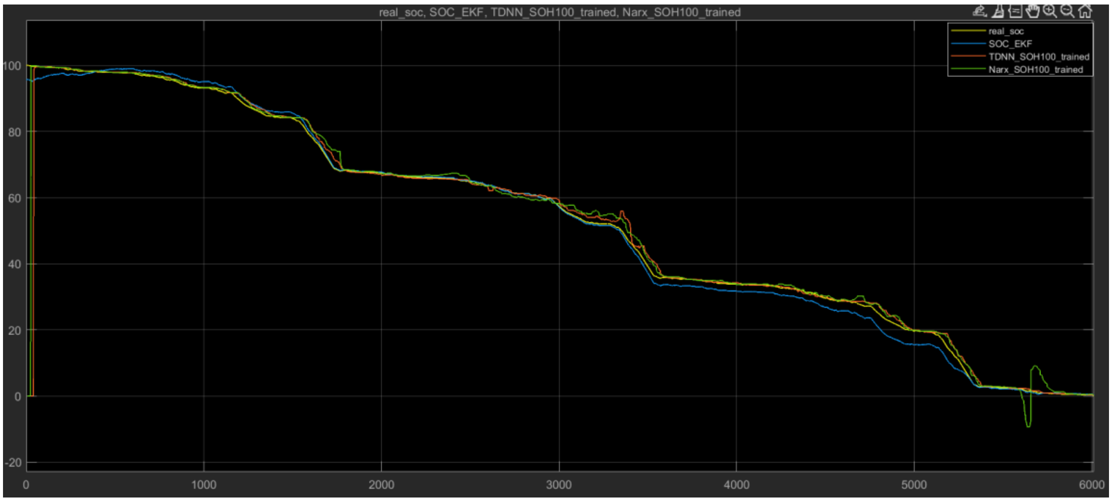


Figure 60. Single loop trained SoC estimation for WLTP at SoH100

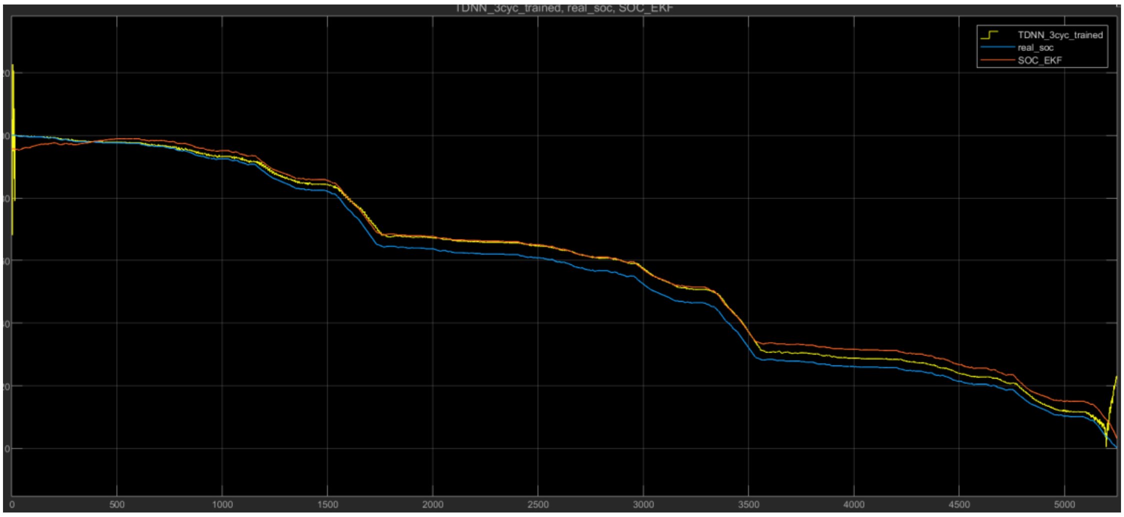


Figure 61. Multi loop trained SoC estimation for WLTP at SoH100

For preparing the actual data test from bench test and vehicle road log data validation, it is necessary to have a comprehensive training in order to cover all using condition, thus the following training assumption has been introduced(figure 62)

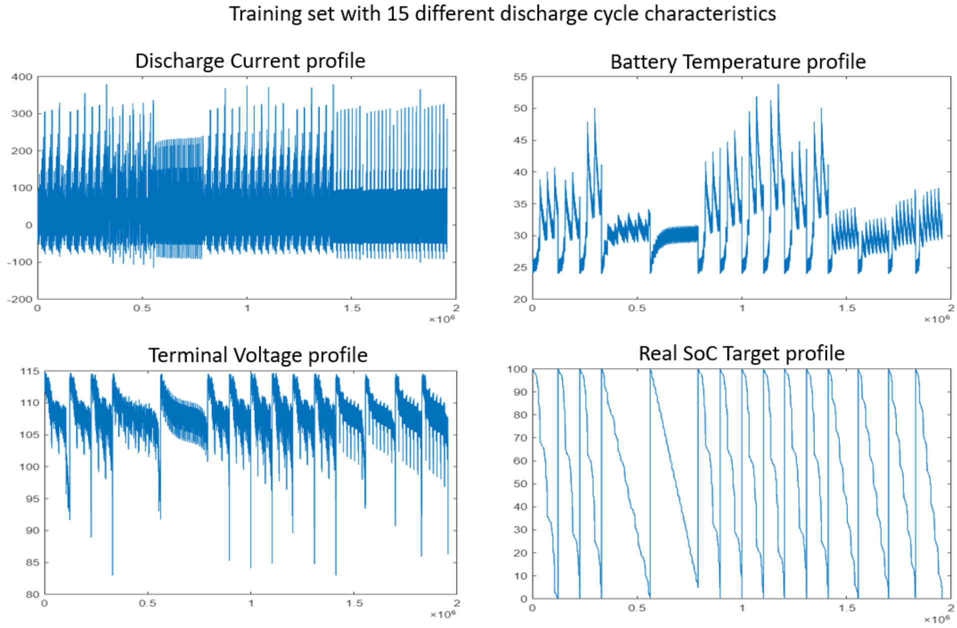


Figure 62. Test profile for experimental validation

Simulation comparison with EKF in validated ECM model environment

The following comparison (figure 63 and figure 64) presents the simulation result under SoH 100% condition using NEDC load profile and SOH 90% condition using WLTP load profile for discharging test.

- EKF has been well tuned for dedicating estimation on actual battery.
- Neural Network has been trained over 15 different cycle for covering learning scope

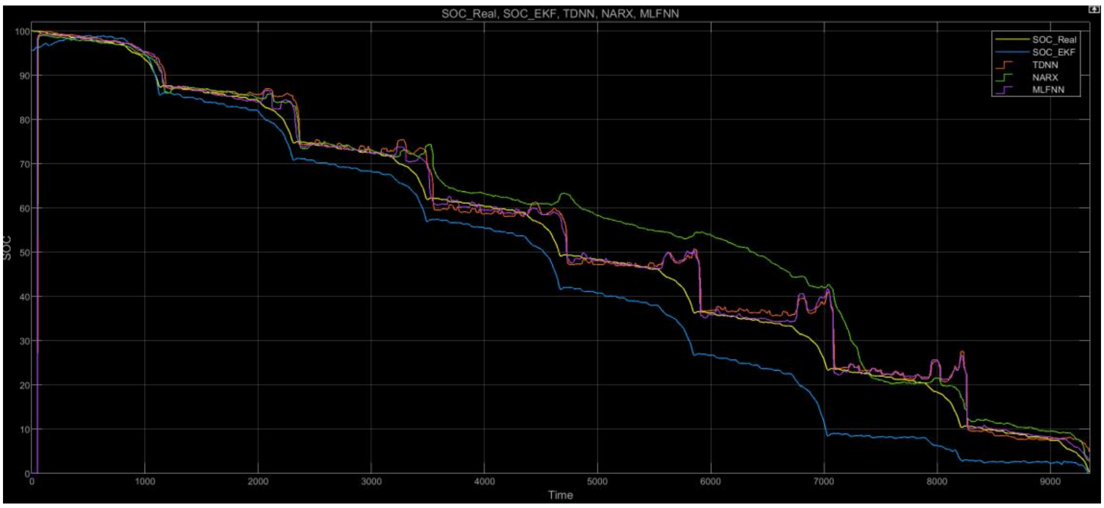


Figure 63. NEDC Test SoC estimation under SoH100%

For different SoH level and further load cycle the result has been calculated using MAE[1] and RMSE[2] comparison for model accuracy comparison

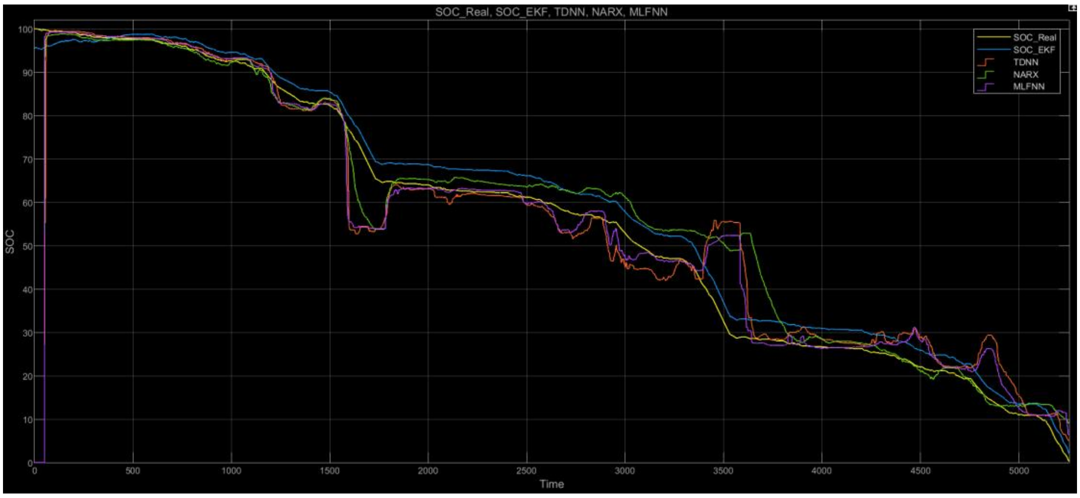


Figure 64. WLTP Test SoC estimation under SoH90%

Discharge test load profile / WLTP						
	SoH 100		SoH96		SoH92	
	MAE	RMSE	MAE	RMSE	MAE	RMSE
EKF	**1.83**	**1.35**	**2.10**	**2.27**	**3.51**	**3.77**
TDNN	4.59	13.26	4.73	13.47	4.69	13.34
NARX	5.93	13.27	5.38	13.52	4.82	13.16
MLFNN	4.53	13.08	4.37	13.07	3.71	12.27

Discharge test load profile / WLTP						
	SoH 90		SoH86		SoH82	
	MAE	RMSE	MAE	RMSE	MAE	RMSE
EKF	**3.90**	**4.16**	5.22	**5.81**	4.90	**6.63**
TDNN	4.17	13.72	4.32	12.99	7.23	15.32
NARX	5.33	13.79	6.02	13.85	7.28	15.20
MLFNN	4.65	13.56	**3.87**	12.73	**4.86**	13.74

Discharge test load profile / NEDC						
	SoH 100		SoH96		SoH90	
	MAE	RMSE	MAE	RMSE	MAE	RMSE
EKF	6.28	**7.41**	4.67	**6.28**	**1.84**	**2.37**
TDNN	2.83	8.65	2.10	8.25	4.94	10.04
NARX	5.45	10.58	5.15	10.72	8.50	13.29
MLFNN	**2.30**	8.36	**1.75**	8.03	4.65	9.69

[1]*mean absolute error (MAE) is a measure of errors between paired observations, it is a common measure of forecast error in time series analysis.*

[2]*Root Mean Squared Error(RMSE) is the square root of Mean Squared Error (MSE). RMSE is a quadratic scoring rule that also measures the average magnitude of the error. It's the square root of the average of squared differences between prediction and actual observation.*

The previous test involves large nonlinear characteristics coming from different cycle, affected mostly from the battery temperature dynamic change due to SoH drop, by reperforming dedicated training target versus estimation loop the neural network has been relieved by the high complexity of prediction requirement which presents extreme good accuracy, but this would not be practical to the real application.

6.2 Validation with battery bench test output and Vehicle data log

Comparison with EKF using actual Bench test data & Vehicle data log

When neural network trained by bench test data of the battery using NEDC discharge cycle and WLTP discharge cycle, the accuracy shows good alignment, as from SoC estimation can be compatible to the EKF with slightly higher error and higher sensitivity.

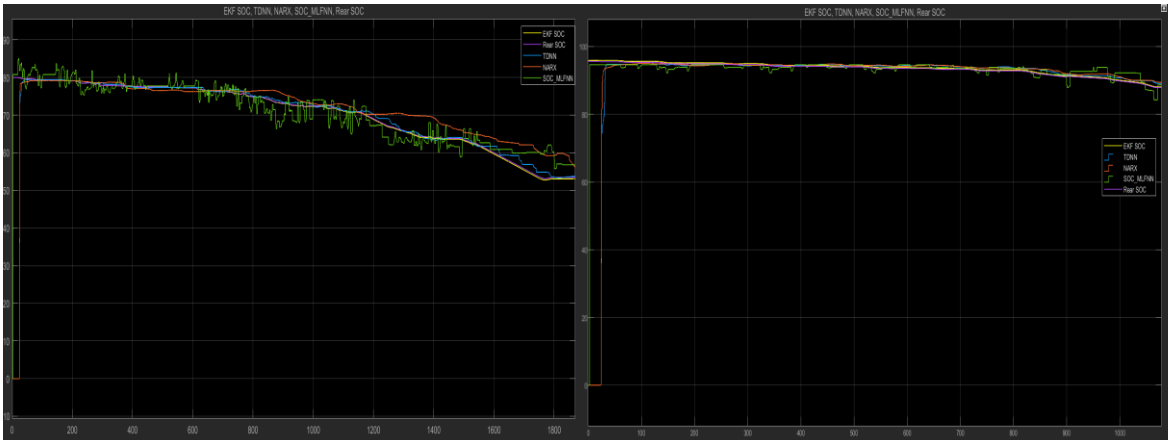


Figure 65. Bench Test Validation TDNN,NARX,MLFNN vs. EKF

6.2.1 Validation Issue of simulation trained Neural Network

Due to the bench test data is only containing limited battery characteristics as it can be observed from figure 65, the trained range is only limited to 90%SOC down to 70%SOC with a fixed SoH condition, the training validated result is not representative for validate the vehicle, in fact when taking this trained network to predict SoC from Vehicle data log, the result has indicated failed estimation.

From Figure 66, previous simulation trained Neural Network has failed to trace the SOC drop from Bench Test data.

Figure 66. Failed predict using simulation trained Neural Network on Bench Test

Due to the difference of Temperature input from actual bench test and vehicle sensor reading, the simulated environment has provided to the training of neural network with a different input pattern, this has led to the temperature input performs with non-correlated weight/bias calculation. Eventually leading to the final output diverted from trained direction.

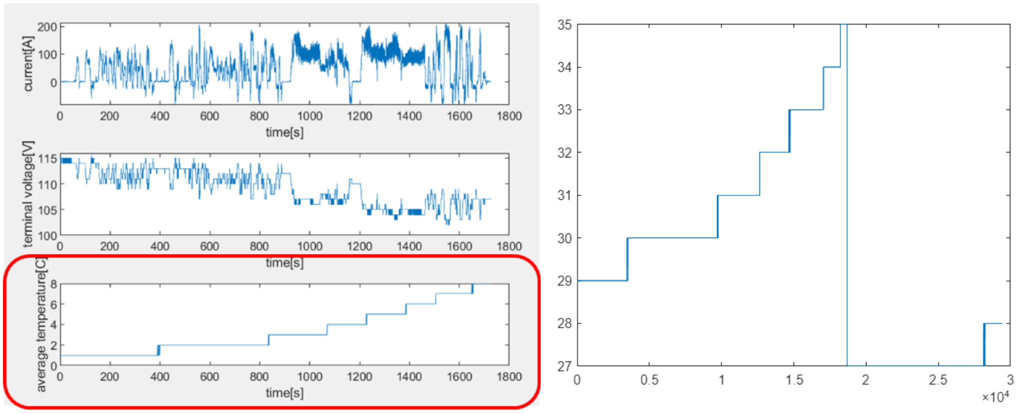


Figure 67. Temperature input with non-correlated pattern on actual test

A simple verification has been performed to identify the conclusion, as to train a TDNN without using temperature as training input using Bench test measurement, the validation using vehicle log data to test the trained network has proven, if Temperature has been decoupled from training input, the TDNN and MLFNN is able to return with good precision estimation on SOC performance, see figure 68.

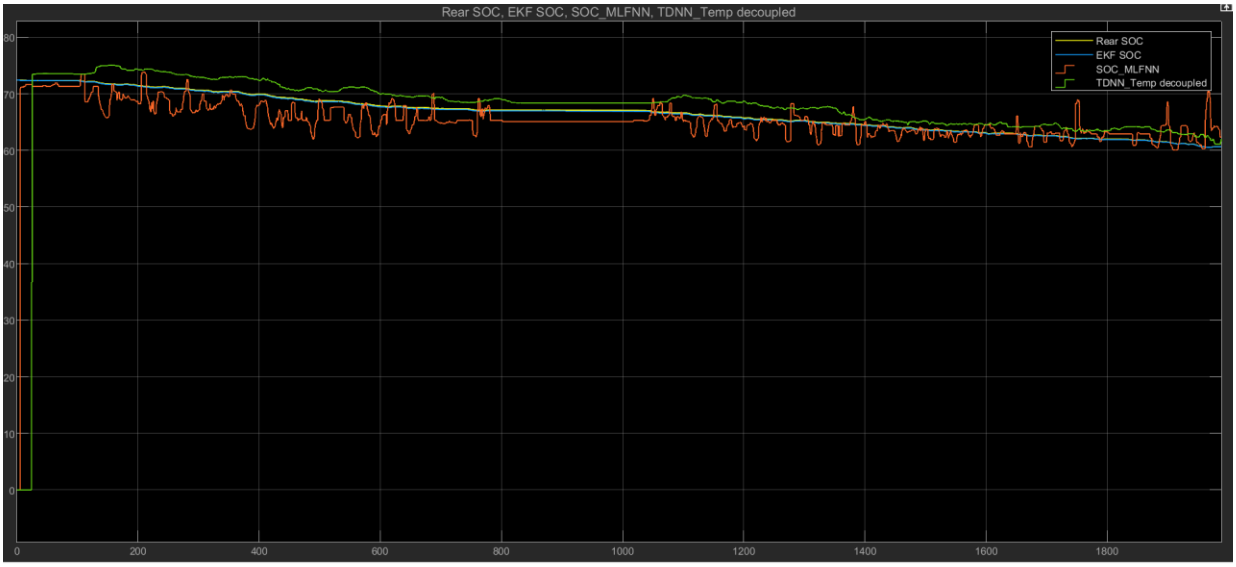


Figure 68. Vehicle data log test 'Urban Road', TDNN with temperature decoupled from input

6.3 Observation of experimental validation result

In this study, a well-validated battery model with well-tuned Extended Kalman filter has been done from another study group, the performance of model base approach is highly recognized from the test result. Which confirm its wide range preference from automotive industry. Although there is still some error but generally it has located within an acceptable range.

By looking at the neural network technique, the simulated environment has confirmed its adaptability from theoretical point of view, following by the experimental test its road block has been exposed evidentaly:

1) When apply Neural Network Techniques to the real application, it has required with correspondence of dynamic behavior of actual received input to have representativeness of what has been trained.
2) Large training data set is required.
3) With increased complexity of neural network, the precision of neural network increases but correspond computation requirement is also required from hardware side.
4) Target Tracing capability can be compatible when further adapting better fit network structure, while the development time can be reduced, the tuning time is not negligible

7 Conclusion

In this work, a battery plant using equivalent circuit method under Simscape/Simulink environment has provided as a theoretical battery inside virtual environment. This approach can be adapted for any on-going development or study use when fitted with proper battery data.

The Extended Kalman Filter approach using output of battery plant is capable to estimate the State of charge, in terms of estimation error a well-tuned extended Kalman filter to a Known, Precise battery modelled can be consider very effective. But the disadvantage remains into the development effort to validate the battery model vs. real battery, model building and related physical test. More complex model has been developed by other teams that is far more dedicate and close to a real battery, the task itself general requires high effort from a research team.

Accurate SOC estimation has been constructed to compare the result with EKF method, with the support of 3 different network layout from back propagation neural network, the neural network can be considered effective from simulation point of view. Temperature impact is considered to evaluate the model robustness, adaptability, and efficiency of SOC estimation under different dynamic loads for several EV drive profiles. And due to that this strategy does not require a dedicated study of battery model, the effort of complex mathematical calculation for a battery model and tuning effort can be reduced.

The neural network method has identified that with a suitable control strategy it is also capable to solve the monitoring issue when implemented a known battery to vehicle where the battery condition is known.

More sophisticated neural network structure can be developed apart from this work. With further comprehensive experimental tests, it would confirm the adaptability of the developed SoC estimation model with SoH impact concluded and this algorithm should be able to adapt further wide control strategy.

8 References:

[1] An Overview of Generic Battery ModelsAla Al-Haj Hussein,Student Member,IEEE, Issa Batarseh, Fellow,IEEE

[2] Battery management system(BMS)simulation environment for electric vehicles, 2016 IEEE, Buccolini, Luca et al.

[3] M. A. Hannan et al.: Neural Network Approach for Estimating SOC of Lithium-Ion Battery Using BSA, pp.1-4

[4] A comparative study of commercial lithium-ion battery cycle life in electric vehicle: Capacity loss estimation. Power Sources 2014;268:658–69.

[5] State of health prediction of lithium-ion batteries based on machine learning: Advances and perspectives Xing Shu,1 Shiquan Shen,1 Jiangwei Shen,1 Yuanjian Zhang,2 Guang Li,3 Zheng Chen,1,3,5, * and Yonggang Liu4, *

[6] Overview of Lithium-Ion Battery Modeling Methods for State-of-Charge Estimation in Electrical Vehicles Jinhao Meng 1 ID , Guangzhao Luo 1,*, Mattia Ricco 2 , Maciej Swierczynski 3 ID , Daniel-Ioan Stroe 2 and Remus Teodorescu 2 ID

[7] State of the Art of Lithium-Ion Battery SOC Estimation for Electrical Vehicles Ruifeng Zhang 1,2,3,* ID , Bizhong Xia 1 , Baohua Li 1 , Libo Cao 2 , Yongzhi Lai 3 , Weiwei Zheng 3 , Huawen Wang 3 and Wei Wang 3

[8] Plett, G.L. Battery Management Systems, Volume II: Equivalent-Circuit Methods; Artech House: Norwood, MA, USA, 2015.

[9] Characteristics of Open Circuit Voltage Relaxation in Lithium-Ion Batteries for the Purpose of State of Charge and State of Health Analysis David Theuerkauf and Lukas Swan *

[10] Kalman Filters versus Neural Networks in Battery State-of-Charge Estimation: A Comparative Study Ala A. Hussein Department of Electrical Engineering, UAE University, Al Ain, UAE

[11] Toward Enhanced State of Charge Estimation of Lithium-ion Batteries Using Optimized Machine Learning Techniques M.A. Hannan1*, M. S. Hossain Lipu2*, Aini Hussain2, Pin Jern Ker1, T. M. I. Mahlia3, M. Mansor1, Afda Ayob2, Mohamad H. Saad2 & Z.Y. Dong4

[12] Implementing an Extended Kalman Filter for SoC Estimation of a Li-Ion Battery with Hysteresis: A Step-by-Step Guide Benedikt Rzepka *, Simon Bischof and Thomas Blank *

[13] Hannan, M.A.; Lipu, M.H.; Hussain, A.; Mohamed, A. A review of lithium-ion battery state of charge estimation and management system in electric vehicle applications: Challenges and recommendations. Renew. Sustain. Energy Rev. 2017,

[14] Plett, G.L. Battery Management Systems, Volume I: Battery Modeling; Artech House: Norwood, MA, USA, 2015

[15] State of Charge Estimation Using Extended Kalman Filters for Battery Management System Carlo Taborelli, Simona Onori, Member, IEEE

[16] Simplified Extended Kalman Filter Observer for SOC Estimation of Commercial Power-Oriented LFP Lithium Battery Cells Tarun Huria and Massimo Ceraolo Università di Pisa Javier Gazzarri and Robyn Jackey MathWorks

[17] K. S. Ng, C.-S. Moo, Y.-P. Chen, and Y.-C. Hsieh, ''Enhanced coulomb counting method for estimating state-of-charge and state-of-health of lithium-ion batteries,'' Appl. Energy, vol. 86, no. 9, pp. 1506–1511, 2009.

[18] M. Coleman, C. K. Lee, C. Zhu, and W. G. Hurley, ''State-of-charge determination from EMF voltage estimation: Using impedance, terminal voltage, and current for lead-acid and lithium-ion batteries,'' IEEE Trans. Ind. Electron., vol. 54, no. 5, pp. 2550–2557, Oct. 2007.

[19] Simplified Extended Kalman Filter Observer for SOC Estimation of Commercial Power-Oriented LFP Lithium Battery Cells, Tarun Huria and Massimo Ceraolo, Università di Pisa, Javier Gazzarri and Robyn Jackey, MathWorks Copyright © 2013 The MathWorks, Inc.

[20] State of Charge Estimation Using Extended Kalman Filters for Battery Management System Carlo Taborelli, Simona Onori, Member, IEEE

[21] Matlab documentation - Extended and Unscented Kalman Filter Algorithms for Online State Estimation

[22] C. Vidal, P. Kollmeyer, M. Naguib, P. Malysz, O. Gross, and A. Emadi, "Robust xEV Battery State-of-Charge Estimator Design using Deep Neural Networks," in Proc WCX SAE World Congress Experience, Detroit, MI, Apr, 2020

[23] State of Health for Lithium-ion Batteries XiangRong Kong ∗ Arman Bonakdarpour ∗∗, Brian T. Wetton ∗ David P. Wilkinson ∗∗ Bhushan Gopaluni ∗∗

[24] D. Bernardi, E. Pawlikowski, and J. Newman, "A General Energy Balance for Battery Systems,"Journal of Electrochemical Society, vol. 132, no. 1, January 1985

[25] Thermal Analysis of LMO/Graphite Batteries Using Equivalent Circuit Models Nadjiba Mahfoudi, M'hamed Boutaous * , Shihe Xin and Serge Buathier

[26] Kalman, R.E. A New Approach to Linear Filtering and Prediction Problems. Trans. ASME J. Basic Eng. 1960, 82, 35–45.

[27] Hannan, M.A.; Lipu, M.H.; Hussain, A.; Mohamed, A. A review of lithium-ion battery state of charge estimation and management system in electric vehicle applications: Challenges and recommendations. Renew. Sustain. Energy Rev. 2017, 78, 834–854

[28] Li-ion Battery Modeling and SOC Estimation Using Extended Kalman Filter Fatma Nur Dişçi(1), Yasser El-Kahlout(2), Abdülkadir Balıkçı (1,2)

[29] Schneider, R.; Georgakis, C. How to not make the extended Kalman filter fail. Ind. Eng. Chem. Res. 2013, 52, 3354–3362

[30] NARX neural networks for sequence processing tasks Eng. Eugen Hristev, June 2012

[31] M. C. Mozer, “Neural net architectures for temporal sequence processing,” in Santa Fe Workshop, 2007, vol. 15.

[32] S. Ingrassia, “Equivalent number of degrees of freedom for neural networks,” Advances in Data Analysis, no. 1, 2007.

[33] M. T. Hagan and M. B. Menhaj, ‘‘Training feedforward networks with the Marquardt algorithm,’’ IEEE Trans. Neural Netw., vol. 5, no. 6, pp. 989–993, Nov. 1994

[34] Zheng, Y.; Ouyang, M.; Han, X.; Lu, L.; Li, J. Investigating the error sources of the online state of charge estimation methods for lithium-ion batteries in electric vehicles. J. Power Sources 2018, 377, 161–188.

[35] Huang, Guang-Bin; Zhu, Qin-Yu; Siew, Chee-Kheong (2006). "Extreme learning machine: theory and applications". Neurocomputing. 70 (1): 489-501.