An Adaptive Neuro-Fuzzy Technique Based SOC Estimation of battery in Hybrid Vehicle

G.Esha #1,V.Bharath Kumar*2, Parveen Mohammed#3

1,2 Assistant Professor in Department of Electrical and Electronics Engineering

1,2 St. Martin's Engineering College, Secudrabad, Telangana, India

gannerlaesha@gmail.com , voruganticee@gmail.com, parveenprofessional991@gmail.com

Abstract—**The advent of Electric vehicles is a major step in building a sustainable energy model. Battery management system is the crux of a hybrid and electric vehicles in market. Online estimation of State of charge is proved to be a challenge in battery management for an electric vehicle. Various Kalman filters with combination of better estimating methods increases accuracy in estimation of state of charge. Improper knowledge of battery management of batteries which leads to performance reduction and it can even lead to practical divergence. Hence adaptive estimation of State of Charge of batteries plays important role in battery management. This paper does a comparative analysis of Extended Kalman filter, Unscented Kalman Filter and Adaptive neuro fuzzy inference system. A new hybrid method combining extended Kalman filter and adaptive neuro fuzzy inference system is been proposed. Adaptive neuro fuzzy inference system, a data driven approach, is given the input from extended Kalman filter for minimizing the error in the estimate value of State of charge. Results show that the error decreased by 70% by using proposed hybrid method over extended Kalman filter to estimate state of charge.**

Keywords—Battery, State of charge(SOC), Battery Management System (BMS) Extended Kalman filter(EKF), Unscented Kalman filter(UKF), adaptive network based fuzzy inference system (ANFIS), Root Mean Square Error(RMSE), Fuzzy Inference System (FIS).

I. Introduction

In the world with ever growing demand for energy, a proper storage with minimal impact on ecosystem is needed to be built. A crucial step in that process is to develop reliable and efficient electric vehicles. Electric vehicle relies on frequent change in charging and discharging of battery in vehicle [1]. Presence of multiple batteries, problems like overcharging of specific batteries, improper load distribution, uneven battery discharge, emerges. Hence a Battery management system is required. A battery management system (BMS) is a collection of electronic components that regulates and monitors the charging and discharging of batteries embedded in electric vehicle [2]. This system monitors the battery parameters and regulates them. Thus, a proper estimation method is required. Estimation methods increases the life span of battery in electric vehicle by protecting from over-discharge and overcharge of battery which leads to improvement in life of battery [3]. Using Kalman filters for this purpose is extensively acknowledged. To study a battery, the battery can be modeled and can be represented as state space equations. The parameters of battery such as voltage, current, temperature can be used as inputs for the equations. Lithium ion battery is preferred over other batteries due to its characteristics which would be useful for a rechargeable battery [4].

Physical characteristics of a battery are considered in direct measurement methods, which includes terminal voltage or impedance . The most prevalent methods include open circuit voltage method, impedance measurement method, terminal voltage method, impedance spectroscopy method. The relation between state of charge (SOC) and open circuit voltage (OCV) is linearized in Open circuit voltage method. Terminal Voltage method depends on the terminal voltage drop during the discharging phase of battery which depends on the internal impedance of battery. Impedance measurement method uses the battery current and voltage to find DC internal resistance of the battery [5].

In Coulomb counting method discharging current of a battery and state of charge of battery of previous time instant are utilized to estimate state of charge and is integrated for accurate estimation of SOC [6]. Coulomb counting and modified Coulomb counting methods are considered as book keeping methods to estimate state of charge.

Many ways are evolving to estimate state of charge in battery and divided into two categories, among them one computes based on mathematical model and another one based on algorithms which are more advanced and precise [7]. Adaptive systems use the data available to narrow down the output to correct value. The adaptive methods comprise of radial basis function (RBF) neural network, back propagation (BP) neural network, support vector machine, fuzzy neural network, fuzzy logic methods, and Kalman filter. Extended Kalman filter and Unscented Kalman filter are used to overcome the drawbacks of the basic Kalman filter [8].

A linear Kalman filter is used for systems where the output varies linearly with the parameter under consideration. It does a prediction step and based on error it estimates the next step. For the application of Kalman filters to nonlinear systems some modifications are needed to be done. Extended Kalman filter linearizes the output at every step by using Taylor expansion. The Jacobian matrices thus obtained are used and the algorithm is executed in an identical procedure as the linear Kalman filter. The Extended Kalman filter involves the addition of a linearizing block at each time step. In the unscented Kalman filter sigma points are taken around the mean of the system and those are used to calculate the prediction step [9].

In an Extended Kalman filter after linearization Kalman filter is implemented in following steps: in first step the following step values, output and covariance error are predicted; then the obtained outputs and Kalman gain are utilized to rectify the present state error. The input of the system is determined in accordance with u(t)=i(t) and the output with y(t)=Vout for a battery model. The Matrices are calculated by partial differentiating f(x,u) with u and g(x,u) with u respectively [10].

ANFIS is a network-structured system adopted in diverse applications, such as control systems, noise cancellation, system identification, output prediction, pattern recognition, and curve fitting. An ANFIS model takes various inputs as fuzzy inputs and propagates them through a neural network. It requires an adequate number of inputs for functioning as intended [11]. State of charge is required for proper safety and maintenance of hybrid vehicle and for estimating SOC, vehicle requires a hybrid method which includes various filters and intelligent techniques.

II. BATTERY MANAGEMENT SYSTEM

Battery is one of the important parts of an electric vehicle requires undivided attention. Since an electric vehicle consists of multiple batteries and components, in this case a system for efficient management is required. BMS provides immediate action to solve the fault, Fault occurrence including irregular charge and discharge and overcharging. Lithium ion batteries are used due to their diversity and huge advantages. A Lithium ion battery is mapped into a mathematical model by measuring its parameters such as voltage, current and constructing state equation for calculating its SOC.

Computation of voltage and temperature requires sensors, hence can be measured relatively easy when compared to state of charge. State of charge among all the parameters is difficult to compute as there is no proper sensor to measure it. SOC is a state parameter which dynamically changes from time to time. Hence various mathematical and analytical algorithms are designed and are in use. The charge in a battery decays with respective active material on electrodes in battery [12]. The detailed description of various algorithms is discussed in further sections.

III. SOC ESTIMATION METHODS

Parameters of battery such as temperature, voltage can be measured directly using appropriate devices. SOC cannot be computed directly due to its non-linearity, it requires certain estimation methods. The SOC can be mathematically interpreted as.

$$SOC = \frac{Q_{at\ time\ t}}{Q_{total}} \tag{1}$$

SOC, as defined by the above equation (1), is the ratio of charge at a given time to the rated capacity where $Q_{at\ time\ t}$ indicates charge at given time and Q_{total} indicates the total charge. SOC estimation forms a basis of battery energy storage system as various other functions are more or less dependent on it. The calculation of other system parameters such as SOH, cell balancing and power calculations take SOC as an input. There are many estimation methods employed currently. Among them the usage of Kalman filters is appropriate for online estimation of the SOC. Kalman filters is an algorithm which takes certain inputs and estimates the output. Kalman filter can be used in vehicle tracking and plays major role in connecting nearby vehicles and to reduce traffic on roads [13]. It is used primarily for linear systems. Hence, various improvements have been made to the algorithm to make the algorithm usable for non-linear systems, and methods like extended Kalman filter and unscented Kalman filter are devised.

A. Extended Kalman filter(EKF)

In extended Kalman filter, at each time step, a linearizing block precedes the Kalman filter algorithm. The non-linear system undergoes local linearization and Kalman filter can be applied [14].

The state space equations of a nonlinear system are given below.

$$X_{k+1} = A_k X_k + B_k U_k + W_k \tag{2}$$

$$Y_k = C_k X_k + D_k U_k + V_k \tag{3}$$

$$X_{(k)} = \frac{SOC(k)}{U_c(k)} \tag{4}$$

X(k) is the state variable

Y(k) equals to V(k) which represents the terminal battery voltage. *W(k)* and *V(k)* represents the process noise and measured noise respectively.

The Model Parameters A(k), B(k), C(k) are demonstrated by equations (5), (6) and (7):

$$A_{(k)} = \begin{bmatrix} 1 & 0 \\ 0 & e^{-\frac{\Delta t}{\tau}} \end{bmatrix}, \tag{5}$$

$$B_{(k)} = \begin{bmatrix} -\frac{\Delta t}{Q_0} \\ R_2\left(1 - e^{-\frac{\Delta t}{\tau}}\right) \end{bmatrix}, \tag{6}$$

$$C_{(k)} = \left(\left[\frac{\partial F(SOC_{(k)})}{\partial SOC_{(k)}} - 1\right] \middle| X_{(k)} = \hat{X}_{(k|k-1)}\right), \tag{7}$$

$$D_{(k)} = R_1 \tag{8}$$

the recursive operation of each step contains the parameters, *Q* and *R*, *W(k)* and *V(k)* are utilized to compute the estimate value *X(k|k-1)* and measured value *V(k)*.

$$x_{k+1} = f(x_k, u_k) + w_k \tag{9}$$

$$y_k = g(x_k, u_k) + v_k \tag{10}$$

f and *g* in equations (9) and (10) are functions of state dynamics. w_k and v_k are process noises.

$$A_{k-1} = \frac{\partial f(x_{k-1}, u_{k-1})}{\partial x_{k-1}}\bigg|_{x_{k-1} = \hat{x}_{k-1}^{+}} \tag{11}$$

$$C_k = \frac{\partial g(x_k, u_k)}{\partial x_k}\bigg|_{x_k = \hat{x}_k^{+}} \tag{12}$$

A_{k-1} from equation (11) is constant Jacobian matrix and C_k from equation (12) is state dependent Jacobian matrix.

Initialization: For $k = 0$, define

$$\hat{x}_0^{+} = E[x_0] \tag{13}$$

In equation (13), $\mathbb{E}[x_0]$ is EKF function. $\hat{x}_0^{+}$ is predicted value of state.

$$P_{\tilde{x},0}^{+} = [(x_0 - \hat{x}_0^{+})(x_0 - \hat{x}_0^{+})^T] \tag{14}$$

$P_{\tilde{x},0}^{+}$ is error covariance calculated from mean error as shown in equation (14). for $k = 1,2, \dots \dots, N$ do

$$\hat{x}_k^{-} = f(\hat{x}_{k-1}^{+}, u_{k-1}) \tag{15}$$

The next state $\hat{x}_k^-$ is computed from the function f as demonstrated in equation (15).

$$P^-_{\tilde{x},k} = A_{k-1}P^+_{\tilde{x},k-1}A^T_{k-1} + P_w \tag{16}$$

Next the error $P^-_{\tilde{x},k}$ is updated based on the previous error $P^+_{\tilde{x},k-1}$ and state

$$L_k = P^-_{\tilde{x},k}C_k^T\left[C_k P^-_{\tilde{x},k}C_k^T + P_v\right]^{-1} \tag{17}$$

Equation (17) demonstrates the calculation of Kalman gain matrix L_k based on the newly calculated error and jacobian matrix from equations (16) and (12) respectively.

$$\widetilde{y_k} = y_k - g(\hat{x}_k^-, u_k) \tag{18}$$

As shown in equation (18), the output $\widetilde{y_k}$ is computed by taking the updated state $\hat{x}_k^-$ and previous output y_k into consideration.

$$\hat{x}_k^+ = \hat{x}_k^- + L_k\widetilde{y_k} \tag{19}$$

Next, the new state $\hat{x}_k^+$ is calculated from Kalman gain matrix and previous state in accordance with equation (19).

$$P^+_{\tilde{x},k} = (I - L_k C_k)P^-_{\tilde{x},k} \tag{20}$$

The new error $P^+_{\tilde{x},k}$ is calculated from the Kalman gain matrix and existing error and it is given by equation (20).

B. *Unscented Kalman filter(UKF)*

On contrary to EKF, Unscented Kalman Filter does not involve linearization of State space equations. In case of UKF, sigma points are computed using nonlinear unscented transform (UT). The mean and error covariance are calculated using sigma points and are updated iteratively. The nonlinear model functions are provided with these sigma points as inputs and a priori estimate of the states and of output signal are obtained. Predicated on the previous values, the mean and covariance are calculated. A feedback network with both the present output value and previous values is used to update the intermediate states and to provide an accurate output value.

In every iteration 2n+1 sigma points and coefficients Wc, Wm are calculated by equations (21) to (25). Here n signifies the number of the number of states.

$$\hat{X}^0_{k-1} = \hat{X}^+_{k-1} \tag{21}$$

$$\hat{X}^i_{k-1} = \hat{X}^+_{k-1} + \sqrt{n+\lambda}\left(\sqrt{P_{k-1}}\right), i = 1,2,\dots\dots,n \tag{22}$$

$$\hat{X}^i_{k-1} = \hat{X}^+_{k-1} - \sqrt{n+\lambda}\left(\sqrt{P_{k-1}}\right), i = n+1, n+2.,2n \tag{23}$$

$$w_0^m = \frac{\lambda}{(n+\lambda)}, w_0^c = \frac{\lambda}{(n+\lambda)} + 1 + \beta - \alpha^2 \tag{24}$$

$$w_i^m = w_i^c = \frac{\lambda}{(2(n+\lambda))}, i = 1,2,\dots\dots,2n \tag{25}$$

where $\lambda = \alpha^2(n+k) - n$ represents the parameter dealing with the distribution of sigma points around their mean. Parameters α and β are assigned with the values of 1 and 0 respectively. The matrix P_{k-1} is decomposed and represented as $\sqrt{P_{k-1}}$. Sigma points are substituted in state-space equations and are computed as given in equations (26) to (28).

$$\hat{x}_k^i = f\left(\hat{x}^i_{k-1}, u_k\right)i = 1,2,\dots\dots,2n \tag{26}$$

$$\hat{X}_k^- = \sum_{i=0}^{2n} w_i^m \hat{X}_k^i \tag{27}$$

$$P_k^- = \sum_{i=0}^{2n} w_i^c\left(\hat{X}_k^i - \hat{X}_k^-\right)\left(\hat{X}_k^i - \hat{X}_k^-\right)^T + Q_k \tag{28}$$

Sigma points of states are propagated substituted in measurement function and output signal is estimated. The values thus obtained are also utilized for computing the covariance and mean of the measurement function, including the cross covariance of the state and measurement functions. It is obtained by equations (29) to (32)

$$\hat{y}_k^i = h\left(\hat{X}_k^i, u_k\right), i = 0,1,2\dots\dots.2n \tag{29}$$

$$\widehat{y_k} = \sum_{i=0}^{2n} w_i^m \hat{y}_k^i \tag{30}$$

$$P_k^h = \sum_{i=0}^{2n} w_i^c\left(\hat{y}_k^i - \hat{y}_k\right)\left(\hat{y}_k^i - \hat{y}_k\right)^T + R_k \tag{31}$$

$$P_k^{fh} = \sum_{i=0}^{2n} w_i^c\left(\hat{X}_k^i - \hat{X}_k^-\right)\left(\hat{y}_k^i - \hat{y}_k\right)^T \tag{32}$$

The sigma points estimate the state and measurement in iterations and the kth iteration of the functions are represented by $\hat{y}_k^i$ and $\hat{x}_k^i$. The mean and covariance of measurement function is represented by $\widehat{y_k}$ and P_k^h and P_k^{fh} signifies the cross covariance of the state $\hat{x}_k^i$ and measurement $\hat{y}_k^i$.

Using the covariance matrices of measurements and states acquired form the above equations Kalman gain is delineated. The calculation of posteriori estimate of the states and state covariance are demonstrated in equations (33) to (35).

$$K_k = P_k^{fh}\left(P_k^h\right)^- \tag{33}$$

$$\hat{X}_k^+ = \hat{X}_k^- + K_k(y_k - \hat{y}_k) \tag{34}$$

$$P_k^+ = P_k^- + K_k P_k^h K_k^T \tag{35}$$

C. *Adaptive Neuro Fuzzy Inference System (ANFIS)*

ANFIS is categorized as a set of adaptive networks similar to the Sugeno fuzzy inference systems. Though the previously described methods give satisfactory estimate of SOC, Occurrence of error still exist. A data driven approach like ANFIS can decrease the disparity in the estimate. The input is driven through a set of rules (fuzzy rules) until the error is minimized [15].

The nonlinear modelling tool will employ adaptive neuro-fuzzy inference systems (ANFIS) which learns the cell characteristics as given by the manufacturer. The curves are approximated within the operating range through fifth order polynomials. Polynomial points are generated to form ANFIS training data and fuzzy rules. ANFIS testing is carried out within, and slightly outside, the training range. ANFIS should be able to generate other curves at different inputs given to system based on weights initialized to hidden layers of adaptive neuro-fuzzy inference system (ANFIS), which is part of the testing procedures and depends on complexity of problem and ambiguity in calculation an adequate number of membership functions, number of layers and number of epochs of ANFIS are chosen.

IV. PROPOSED SYSTEM AND RESULTS

Using a hybrid method, a combination of two methods, give better estimate over using a single method.

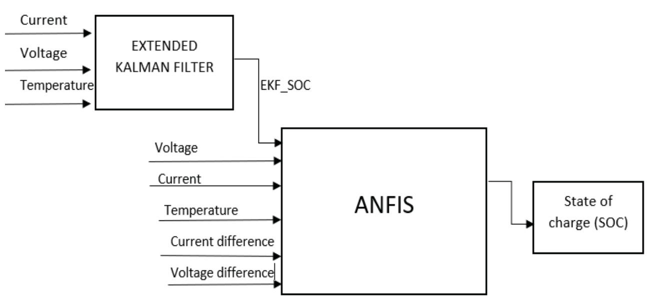

Fig.1. Block diagram

Fig.1 depicts the block diagram or work flow for modification of state of charge estimated from extended kalman filter. The SOC given by the EKF along with other battery parameters are given as inputs to ANFIS. For estimating the state of charge three methods are used individually

1. EKF
2. UKF
3. EKF in combination with ANFIS.

MATLAB Simulink is used to simulate EKF and UKF. The ANFISEDIT of MATLAB is used to compute ANFIS which aids in improving state of charge.

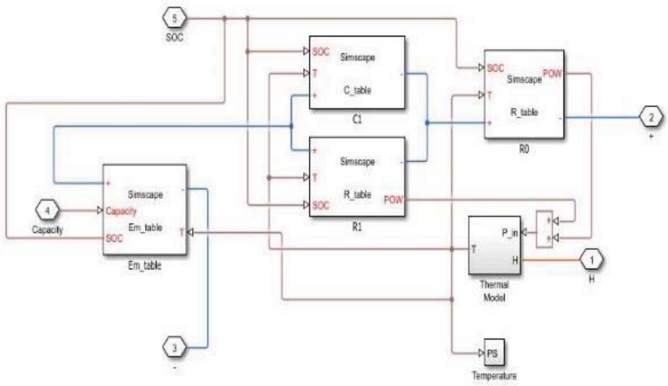

Fig.2 Equivalent circuit model using simscape

Battery equivalent first order RC model is modelled using SIMSCAPE as shown in Fig.2 Values of individual parameters are loaded in workspace with respect to temperature and SOC of resistance (R) & capacitance (C).

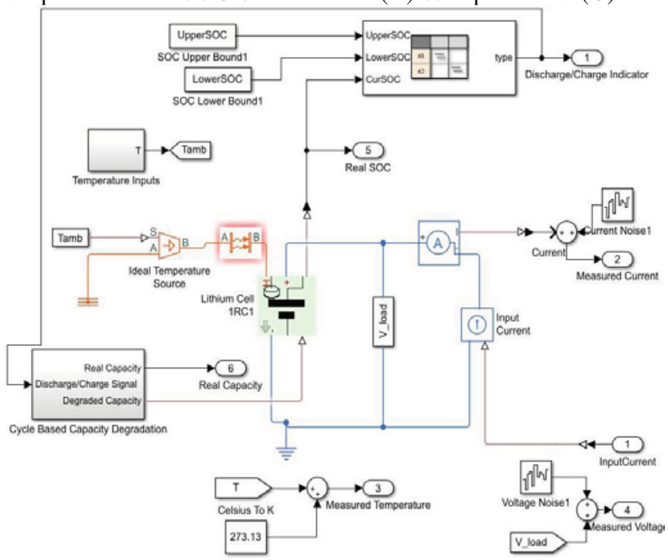

Fig.3 Electro-thermal model of the battery

Fig.3 illustrates battery equivalent of one stage resistor and capacitor (RC) (Lithium cell 1RC) connection with input current source and with thermal model for temperature measurement.

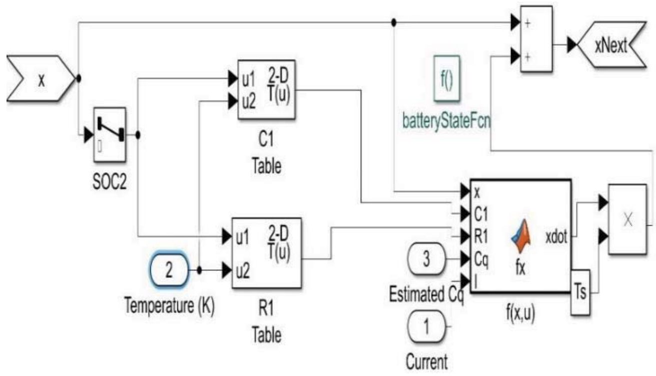

Fig.4 State function Simulink model

The discrete space model state equation of Kalman filter is modelled using look up table of individual R &C parameters and Simulink function used as script file as shown in Fig.4.

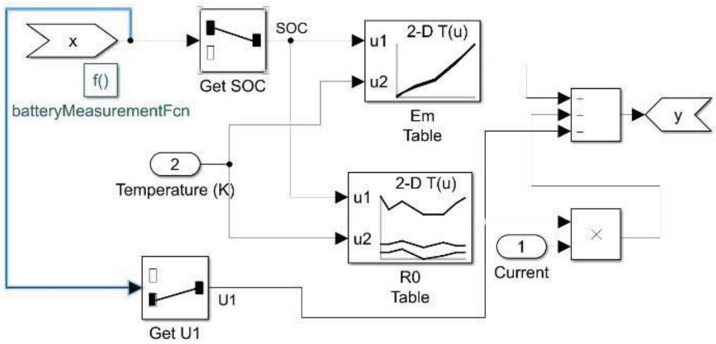

Fig.5 Measurement function Simulink model

The discrete space model measurement equation is modelled using look up table of individual R &C parameters at SOC values as shown in Fig .5.

A. Combined method:

Current, voltage, temperature, SOC affects the output of the battery. The SOC calculated from EKF is given as an input to ANFIS. For implementing ANFIS model in the proposed hybrid system the parameters like temperature, SOC, current, voltage, current difference and voltage difference are provided as inputs. Membership functions are limited to 2 which reduces ambiguity in calculations.100 data sets comprising of both inputs and outputs is considered which creates a FIS (fuzzy inference system) file. The resulting trained model is further connected to fuzzy controller and fis file loaded in fuzzy controller.

The simulation model of the system is shown in Fig.6.The state function and measurement function are used to calculate state of charge using extended Kalman filter and unscented Kalman filter. Neuro-fuzzy system trained with three internal parameters of battery which are required to calculate of state of charge. The resultant SOC obtained from different methods is compared in terms of Root Mean Square Error calculated using equation 36.

$$\text{RMSE} = \sqrt{\frac{\sum_{i=1}^{n}(\text{predicted SOC value} - \text{actual SOC value})^2}{n}} \quad (36)$$

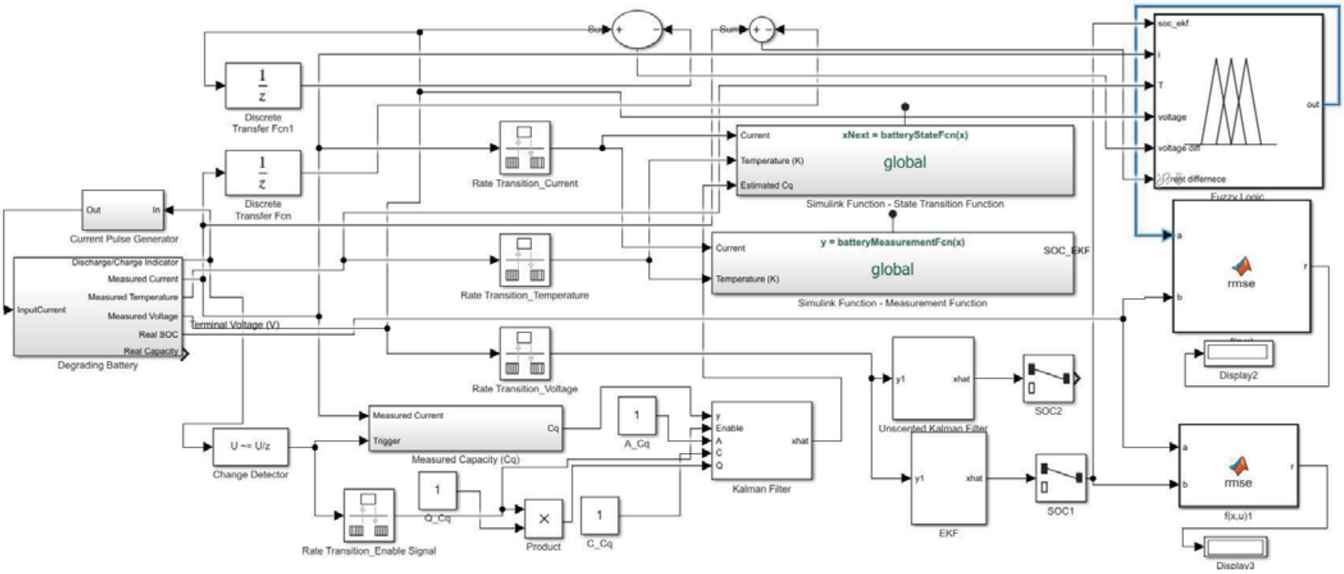

Fig.6 Simulink model for estimation of SOC using EKF & EKF with ANFIS

B. Simulation Results:

Voltage, current and temperature are measured from battery and uploaded in workspace of matlab are provided as inputs for extended Kalman filter and unscented Kalman filter.

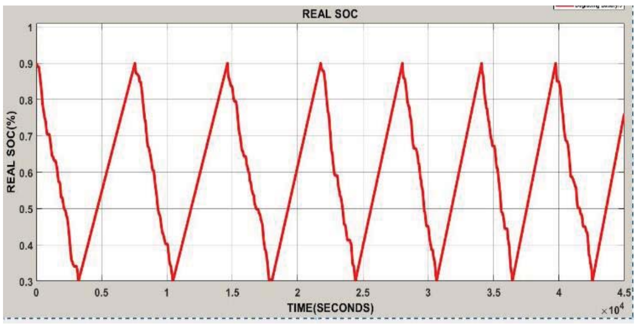

Fig.7 Real SOC (%) vs Time(sec)

The plot against real SOC and time in Fig.7 gives real SOC of battery and displays charge and discharge cycle of charge in battery.

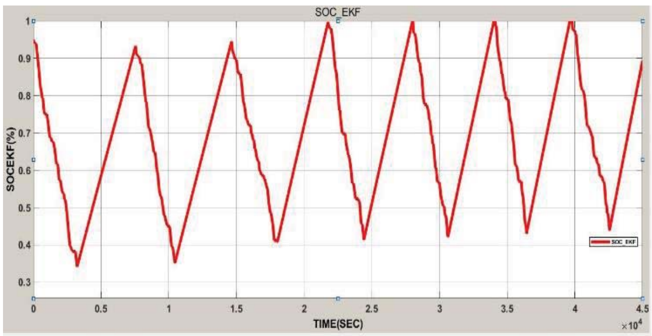

Fig.8 SOC estimated using EKF (%) vs time(sec)

For estimating state of charge in battery using EKF and UKF parameters like voltage, temperature are considered as inputs and current in battery serves as state parameter connected to state function and measurement function model. The plot against EKF _SOC and time in Fig.8 gives state of charge of battery estimated using EKF and triangular wave form conveys charging and discharging of battery.

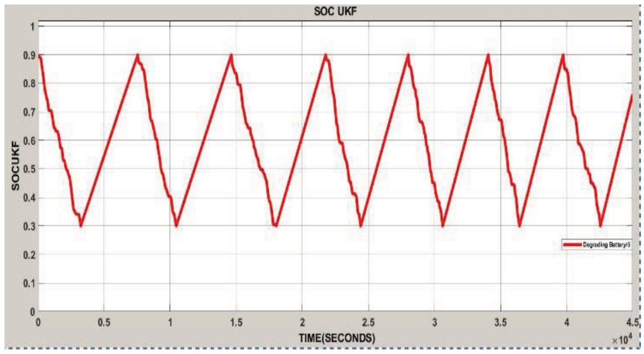

Fig.9 SOC estimated using UKF (%) vs time (sec)

Fig.9 represents state of charge of battery estimated using unscented Kalman filter and charging cycle and discharging cycle of battery is depicted as triangular wave form.

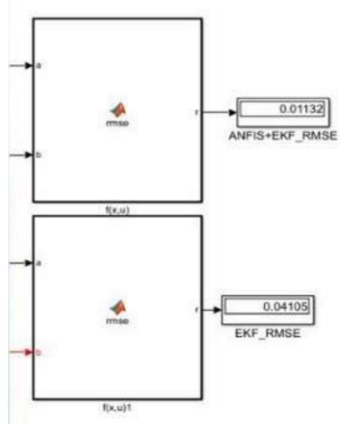

Fig.10 RMSE of EKF and EKF+ANFIS

Root mean square error is evaluated by coding (eqn-36) in Simulink function block as shown in Fig.6 . Fig.10 illustrates root mean square error of ANFIS combined EKF and EKF alone using gauss function as membership function with 20 epochs. It concludes that root mean square error value of EKF is greater than root mean square error value of EKF with ANFIS.

C. Comparison between EKF and EKF-ANFIS:

Table 1 Comparison Based On RMSE

Training Set	Estimation Method	Root Mean Square Error
100	EKF_SOC	0.04105
100	EKF+ANFIS_SOC	0.01132

Table 1 shows improvement in estimating state of charge using EKF combined with ANFIS than using extended Kalman filter alone. By changing various type of membership functions and epochs it is possible to reduce root mean square error of extended Kalman filter.

Extended Kalman filter (EKF) computes till second order Taylor series to update covariance, which produces less precise in estimating state of charge where as UKF compute to higher order of Taylor series leads to more precision in estimation of state of charge. UKF filter uses unscented transform which makes robust to noise but costlier when compared to ANFIS which get trained with training parameters. Based on comparison three methods among them ANFIS combined EKF provides better results in estimation and compatible to utilize in this emerging market.

V. CONCLUSION

Kalman filters are simulated in MATLAB for estimation of state of charge in a battery. A near investigation of Extended Kalman filter and Unscented Kalman filter is presented in the paper. Unscented Kalman filter is demonstrated to appraise the blunder with more precision than the EKF. UKF required huge number of sigma points which cost more than EKF and need more run time.

Adaptive neuro fuzzy inference system (ANFIS) which is more efficient and economical than UKF. It has been trained with a 100 data sets and 2 membership functions for each input and output. EKF is good choice for estimating linear problems but when the internal parameters of battery are inappropriate the performance can become unpredictable and degrading. State of charge predicted using EKF combined with ANFIS gives minimized Error and High Accuracy over SOC prediction using EKF. Comparative study between EKF and EKF assisted ANFIS evaluated based on RMSE value. Thus, utilizing the hybrid method, precision and accuracy of state of charge estimation can be improved in a cost-effective manner.

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