International Journal of Aquatic Science
ISSN: 2008-8019
Vol 12, Issue 02, 2021

State Estimation Of Battery Management System Using Particle Filter

S. Sneha[1], D. Jayaprasanth[2]

[1]PG Scholar, Department of Instrumentation and Control Systems Engineering, PSG College of Technology, Coimbatore, India
[2]Assistant Professor (Senior Grade), Department of Instrumentation and Control Systems Engineering, PSG College of Technology, Coimbatore, India

Abstract: The degradation of the environment and severe energy crisis made the government to pay attention to techniques which results in minimum emission. In such cases, batteries play a main role because they have high energy density and long service life. Batteries are considered to be the best alternative for reducing the emission released. Hence batteries are environmentally friendly in nature. A Battery Management System (BMS) is required in order to maintain a good performance of the battery. Battery Management System involves in continuously tracking the states of the battery and also monitoring the states. Thus, with the help of BMS, the dynamic behavior of the batteries can be analyzed continuously. An estimator serves to be a decision rule which estimates the parameters of state based on the observations taken. Particle filter is one such estimator which is based on Monte Carlo methodology and can be applied for both Gaussian and Non-Gaussian distributions. A common problem faced is the phenomenon of degeneracy where the weights of the particles tend to be negligible after few iterations. This can be overcome by the proper choice of proposal density which plays a vital role and also by the process of resampling. When the particle filter algorithm involves the resampling process, it is referred as Sequential Importance Resampling Particle Filter (SIR-PF). This paper deals with the implementation of SIR-PF for estimating the states of the battery and analyzing the performance of the filter.

Keywords: Battery; Particle Filter; Resampling; State Estimatio

1. INTRODUCTION

State Estimation is a branch of statistical theory which involves in estimating the parameter values. These values are based on measured data which contains a random component. The parameters in turn indicates the physical setup in such a way that the parameter values affect the distribution of the measured data. A state estimator helps in approximating the unknown states with the help of measurements. State estimation involves a system to have accurate knowledge about its current states and then consequently make informed decisions while choosing future control inputs. Hence state estimation is a necessary condition for a control to be effective and the general block diagram of the state estimation scheme is shown in Fig. 1.

State estimation and filtering are considered to be the most important tools of engineering. In order to control an industrial plant or a process efficiently and in order to ensure safety within the plant, it is important to know the full states of the plant that indicates the complete dynamics.

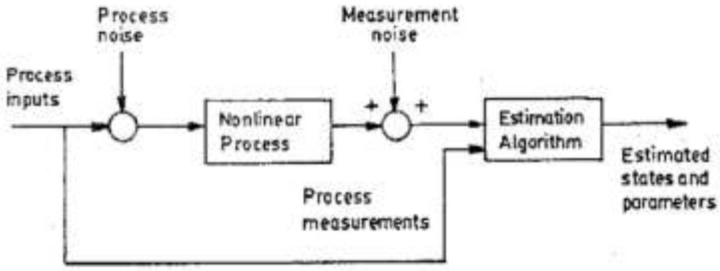

Fig. 1. Block diagram of state estimation scheme.

But in many situations, it is not possible to measure all the states of a process with the help of sensors. This is because of the difficulty of incorporating the sensors into the plant. In such cases, state estimation plays an important role by producing an estimate of the entire system with the available limited measurement data. Thus, state estimation is an important pre-requisite for the safe and efficient operation of a process. Filtering is a technique of estimating the states of a system from the available observations. Such states can be used in various fields of applications like fault diagnosis, monitoring and control techniques in the field of process engineering.

The estimation of unmeasured states leads to better control of the process as the knowledge of all states are known. There are various methods of estimation which includes Kalman filter (KF), Extended Kalman filter (EKF), Unscented Kalman filter (UKF), Particle filter (PF), etc. Based on the presence of non-linearities and the nature of the process, a suitable estimator is chosen in order to estimate the states of the system.

The Bayesian approach is based on constructing a posterior probability density function (pdf) which is based on all the available information which includes the set of received measurements [8]. An optimal estimate of the state is obtained from the pdf which is also a measure of the accuracy of the estimate which is obtained. In some cases, an estimate is required every time when a measurement is received. In such cases, recursive filter happens to be a convenient solution. Rather than processing a measured data in batch manner, a recursive filter involves in processing the data sequentially. Hence it is not necessary to store the complete data set or to reprocess the existing data if a new measurement is available.

For a linear system, Kalman filter is considered as the optimal filter in solving a state estimation problem. For a non-linear system, various filters can be applied based on the system performance and the accuracy of estimation. An extension of Kalman filter called the Extended Kalman Filter (EKF) is used in non-linear system for solving a state estimation problem. A main disadvantage in using EKF is that, the analytical computations involve Jacobians which makes the computation tedious while applying it to higher order systems.

Another Kalman based estimator called the Unscented Kalman Filter (UKF) can be applied which involves a deterministic sampling technique called as the Unscented Transformation (UT) technique. This technique is applied in order to generate more accurate estimation results. UKF overcomes the disadvantage of EKF since no Jacobians are involved. Hence UKF can also be called as the Derivative free Kalman filter. Both the EKF and UKF can be applied to systems which involves only Gaussian distribution.

While considering the non-linear systems, both the process and the measurement noises are assumed to be Gaussian. But once it is propagated through the non-linear equations, the distribution evolves into a non-Gaussian distribution. To overcome such limitations, Particle filter (PF) can be used. Particle filters can be applied to systems involving Gaussian as well as non-Gaussian distribution.

This paper focuses on estimating the states of a battery using Particle Filter (PF). Particle filter belongs to the Sequential Monte Carlo methodology. The main idea of the Particle filtering is to represent the posterior density function by a set of random samples. These samples are associated with their own weights. The estimates are computed based on these samples and weights [3].

The Particle filter is one such estimator which is based on probability techniques. The Particle filter also called as the Sequential Importance Resampling (SIR) filter is useful in systems which deals with non-linearities and also in systems in which non-Gaussian features exists. SIR filters belong to the class of Bayesian filters. Bayesian filters provides a general framework for dynamic state estimation problems. The Bayesian approach is based on constructing the probability density function (PDF) of the states based on the available information.

2. Battery Management System

Batteries play an important role in energy storage systems of electric vehicles and smart grids. This is because batteries possess long service life, high energy density and are also environmentally friendly in nature. Due to the rising energy crisis and environmental degradation, much attention has to be paid for the energy saving and emission reducing techniques [2]. Therefore, a Battery Management System (BMS) is essential to continuously track the dynamic behavior of the battery and also to monitor its operation states [6]. The main purpose of a Battery Management System is to protect the battery while it operates outside its safe operating area.

2.1 System Description

To design an efficient battery management system a thorough knowledge about the battery system is essential. The electrical modeling is one type of battery model representation. Due to the complexity of the nonlinear electrochemical processes, it is difficult to represent the dynamics of the model accurately. Hence a model-based description of the system is used.

2.2 State Space Model

A state space model represents the mathematical model of a physical system in terms of input, output and state variables. The state space model provides an idea about the internal state of the system [6]. A state space model of a battery consisting of V_{cb}, V_{cs} and V_o as state variables is considered [7]. The estimation methods require the complete knowledge about the model of the system which is considered.

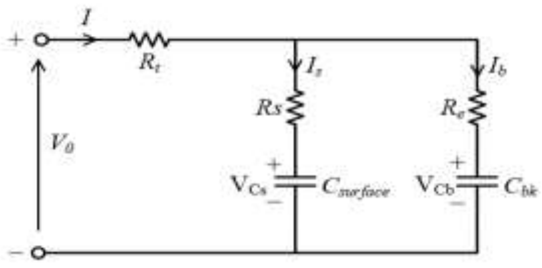

Fig. 2. Schematic Representation of Battery model.

The model as shown in Fig. 2 contains a bulk capacitor C_{bk} which acts as the energy storage component in the form of charge. A capacitor C_{surf} models the surfaces capacitance and the effects of diffusion within the cell. The resistance across the terminal surface, surface resistance and end resistance are R_t, R_s and R_e respectively. The voltages across both the capacitors are represented as V_{cb} and V_{cs} respectively.

International Journal of Aquatic Science
ISSN: 2008-8019
Vol 12, Issue 02, 2021

The states of the battery are represented as differential equations as follows:

$$\dot{V}_{cb} = \mathrm{A.I.}R_s + \mathrm{A.}V_{cs} - A.V_{cb} \quad (1)$$

$$\dot{V}_{cs} = \mathrm{B.I.}R_e - \mathrm{B.}V_{cs} + \mathrm{B.}V_{cb} \quad (2)$$

$$\dot{V}_o = -(\mathrm{A}+\mathrm{B})V_{cb} + (\mathrm{A}-\mathrm{B})V_o - A(R_t + D - 0.5R_s)I + B(R_t + D + 0.5R_e)I$$
(3)

Where $\mathrm{A} = \frac{1}{C_{bk}(R_e+R_s)}$ (4)

$\mathrm{B} = \frac{1}{C_{surf}(R_e+R_s)}$ (5)

$\mathrm{D} = \frac{R_eR_s}{R_e+R_s}$ (6)

In Control theory, a lumped linear network can be written in the form as

$$\dot{x}(t) = Ax(t) + Bu(t) \quad (7)$$

$$y(t) = Cx(t) + Du(t) \quad (8)$$

Hence the state space representation of the model is as follows:

$$\begin{bmatrix} \dot{V}_{cb} \\ \dot{V}_{cs} \\ \dot{V}_o \end{bmatrix} = \begin{bmatrix} -A & A & 0 \\ B & -B & 0 \\ (-A+B) & 0 & (A-B) \end{bmatrix} \begin{bmatrix} V_{cb} \\ V_{cs} \\ V_o \end{bmatrix} + \begin{bmatrix} \mathrm{A}R_s \\ \mathrm{B}R_e \\ A(-R_t - D + 0.5R_s) + B\,(R_t + D + 0.5R_e) \end{bmatrix} I \quad (9)$$

The values of various parameters of the battery are shown in Table 1.

Table 1.
System Parameters

Parameter	Value
End resistance (R_e)	0.00375 Ω
Surface resistance (R_s)	0.00375 Ω
Terminal resistance (R_t)	0.002745 Ω
Bulk capacitor (C_{bulk})	88372.83 F
Surface capacitor (C_{surf})	82.11 F

On substituting the above parameter values, the values of A, B and C are calculated as

$$A = \begin{bmatrix} -0.001508 & 0.001508 & 0 \\ 1.6238379 & -1.6238379 & 0 \\ 1.6223291 & 0 & -1.6223291 \end{bmatrix} \quad (10)$$

$$B = \begin{bmatrix} 0.0000056757847553 \\ 0.006089392278651 \\ 0.010542685882214 \end{bmatrix} \quad (11)$$

$$C = \begin{bmatrix} 0 & 0 & 1 \end{bmatrix} \quad (12)$$

A transfer function is a mathematical function which relates the output or a response of a system. The transfer function of the considered battery model is given as

$$G(s) = \frac{0.01054s^3 + 0.0171s^2 + 2.981*10^{-5}s}{s^4 + 3.248s^3 + 2.637s^2 - 1.144*10^{-18}s} \quad (13)$$

3. State Estimation

3.1. Methods of Estimation

The state estimation techniques can be broadly classified into the following two categories:

- Constrained State Estimation
- Unconstrained State Estimation

The Unconstrained state estimation techniques are further classified based on the presence of non-linearities as follows:

- Linear systems
  - Kalman filter
- Non-linear system
  - Extended Kalman filter
  - Unscented Kalman filter
  - Particle filter

An estimator serves to be a decision rule in which the sequence of observations is taken as arguments and evaluates the value for a parameter of state. The performance of the estimator varies according to the nature of the system. Hence a complete knowledge about the dynamics of the system is essential in order to choose the efficient estimator for the process. To obtain a desired estimator, it is also essential to first determine a probability distribution from the measured data.

3.2.Kalman filter

Kalman filter is considered as the optimal filter which describes a recursive solution to the discrete-data linear fitting problem. Due to the wide area of applications of the Kalman filter, it is extensively used in areas of autonomous or assisted navigation. The Kalman filter is a set of mathematical equations which provides an efficient recursive(computational) means to estimate the states of a process. It also minimizes the mean of the squared error. This particular filter supports the estimation of past, present and future states. The filter also estimates the states when the precise nature of the modeled system is unknown.

The estimation process of Kalman filter consists of two steps:

- Prediction
- Correction

The first step includes the prediction phase where the states are predicted with the dynamic model. An observation model is used for correction so that the error covariance of the estimator is minimized. Since the error is minimized and, in some case, completely the error is reduced, hence the Kalman filter is said to be an optimal estimator. The procedure is repeated for each time step with the state of the previous time step as the initial value. Hence Kalman filter is said to be a recursive filter.

International Journal of Aquatic Science
ISSN: 2008-8019
Vol 12, Issue 02, 2021

The Kalman filter's operation is based on propagating the mean and the covariance of the state through time. The prediction phase uses the estimates of the state from the previous time step to produce the estimate of the state at the current time step. The correction phase involves in combining the current a priori prediction and the current observation information. This is done in order to refine the state estimate. Kalman filter is more simple, robust and optimal but it is a linear filter. Hence it cannot be applied for the estimation of states in case of a non-linear system.

3.3 Extended Kalman Filter

A Kalman filter that linearizes about the current mean and covariance is termed to be Extended Kalman Filter (EKF). In specific it can be said that the EKF involves in linearizing the nonlinear function around the current estimate. Therefore, EKF is one among the many non-linear filters available which finds its application on non-linear estimation and machine learning. The application of EKF also includes the estimation of the state of non-linear dynamic system, estimation of the parameters of a non-linear system and also dual estimation [1].

EKF also has two phases: prediction and update**.** The prediction phase uses the estimates of the state from the previous time step to produce the estimate of the state at the current time step. The update phase uses the measurement information at the current time step which is used in refining the prediction. The analytical computations involve Jacobians which makes the computation tedious while applying it to higher order systems.

3.4 Need for Particle Filter

Particle filter overcomes all such limitations and can be used for both Gaussian and Non-Gaussian distributions. When a Particle filter is implemented on a non-linear system, it does not require any linearizing techniques thereby making the estimation of the state easier.

4. Particle filtering

For various application areas in order to model the dynamics of a physical system accurately, it has become essential to include Non-Linearity and Non-Gaussian elements. Also many problems in science requires the estimation of states that varies with time using a sequence of noisy measurements. Particle filter is one such filtering technique which can be applied to both the Non-Linear and Non-Gaussian systems. Particle filter is based on the Sequential Monte Carlo method. The basic idea involves the recursive computation of relevant probability distributions by the concept of Importance Sampling [4] and approximation of probability distributions with discrete random measures [5]. The main idea of the Particle filtering is to represent the posterior density function by a set of random samples. These samples are associated with their own weights. The estimates are computed based on these samples and weights. It is also called as Bootstrap filtering, Condensation algorithm and the Survival of the fittest algorithm.

1.1. Sequential Importance Sampling Particle Filter (SIS-PF)

The SIS-PF is also a Monte Carlo (MC) method. The key idea is to represent the required posterior density function by a set of random samples with associated weights. As the number of samples becomes large, this MC characterization becomes an equivalent representation to the usual functional description of the posterior pdf, and the SIS filter approaches the optimal Bayesian estimate.

Let us consider the random measure that contains $p(x_{0:k}|\ z_{1:k})$ as the posterior pdf. It contains a set of points with its associated weights represented as $\{w_k^i, i = 1, \dots, N_s\}$ and the set of all states up to time k as $x_{0:k} = \{x_j, j = 0, \dots, k\}$. The weights are normalized to be $\sum_i w_k^i = 1$.

The posterior density at k is approximated as

$$p(x_{0:k}|\ z_{1:k}) \sim \sum_{i=1}^{Ns} w_k^i \delta\,(x_{0:k} - {x_{0:k}}^i) \qquad (14)$$

The Importance Sampling is the principle that lies behind the concept of choosing the weights for the algorithm. If the probability density $p(x) \propto \pi(x)$ from which it is difficult to draw the samples, but for $\pi(x)$ it can be evaluated, then let $x^i \sim q(x), i = 1, \dots, N_s$ be the samples which can be easily generated from the proposal density $q(.)$ which is called as Importance density. The weighted approximation to the density $p(.)$ is given by

$$\sum_{i=1}^{Ns} w_k^i \delta\,(x - x^i) \qquad (15)$$

where $w^i \propto \frac{\pi(x^i)}{q(x^i)}$ is the normalized weight of the particle.
The weights are represented as

$$w_k^i \propto \frac{p({x_{0:k}}^i|\ z_{1:k})}{q({x_{0:k}}^i|\ z_{1:k})} \qquad (16)$$

The weight update equation is obtained as

$$w_k^i \propto \frac{p\left(z_k\middle|x_k^i\right)p\left(x_k^i\middle|x_{k-1}^i\right)p({x_{0:k-1}}^i|z_{1:k-1})}{q(x_k^i|{x_{0:k-1}}^i,z_{1:k})q({x_{0:k-1}}^i|z_{1:k-1})} \qquad (17)$$

$$w_k^i = w_{k-1}^i\ \frac{p\left(z_k\middle|x_k^i\right)p\left(x_k^i\middle|x_{k-1}^i\right)}{q(x_k^i|{x_{0:k-1}}^i,z_{1:k})} \qquad (18)$$

The posterior filter density is approximated to be as follows

$$p(x_k|\ z_{1:k}) \sim \sum_{i=1}^{Ns} w_k^i \delta\,(x_k - {x_k}^i) \qquad (19)$$

As N_s reaches infinity, the approximation approaches the true posterior density $(x_k|\ z_{1:k})$.

4.1. Degeneracy Phenomenon

A common problem faced by the SIS-PF is degeneracy phenomenon. After few iterations, the weights of few particles will tend to be negligible. This results in degeneracy issue where a large computational effort is made to update the particles whose contribution to the approximation is almost zero [9]. This degeneracy phenomenon is clearly an undesirable effect in the concept of Particle filters. If degeneracy occurs, then the variance tends to be very large. The increase in variance will result in the increase of discrepancy between the true distribution and the importance function [10].

There are two ways from which this issue can be eliminated.

- Good choice of importance density
- Use of resampling

International Journal of Aquatic Science
ISSN: 2008-8019
Vol 12, Issue 02, 2021

Therefore, to overcome this phenomenon, the technique of resampling is introduced. When an SIS-PF is subjected to resampling techniques then it is called as Sequential Importance Resampling Particle Filter (SIR-PF).

4.2. Resampling

The basic idea that revolves around the concept of resampling technique is to eliminate the particles which have smaller weights and to concentrate more on particles with larger weights. The resampling step involves in generating a new set $\{x_k^{i*}\}_{i=1}^{Ns}$ by resampling N_s times from an approximate discrete representation which is given by

$$p(x_k|\ z_{1:k}) \sim \sum_{i=1}^{Ns} w_k^i \delta\,(x_k - {x_k}^i) \qquad (20)$$

So that $Pr(x_k^{i*} = x_k^j) = w_k^j$. (21)

Though resampling reduces the effect of degeneracy problem, it introduces other practical problems. One such problem occurs when the particles with high weights are statistically selected many times. This may lead to diversity among the particles which results in a resultant sample containing many repeated points. This problem is called as the sample impoverishment.

4.3. SIR-PF Algorithm

The SIR-PF algorithm is as follows:

1. For $i = 1{:}\,N_s$
   - Draw a sample from the proposal density
     $$x_k^i \sim P(x_k^i|x_{k-1}^i)$$
   - Calculate the importance weight
     $$w_k^i = P(z_k|x_k^i)$$

End

2. Calculate total weight
$$t_w = SUM\{w_k^i\}_{i=1}^{N_s}$$
3. Normalization
$$\widetilde{w}_k^i = \frac{w_k^i}{t_w}$$
4. Resample to get an updated predicted state
$$\{x_k^i, w_k^i\}_{i=1}^{N_s} = RESAMPLE\{x_k^i, \widetilde{w}_k^i\}_{j=1}^{N_s}$$

4.4. Advantages of SIR-PF

The advantages of the generic particle filter are as follows:

- No restrictive assumptions are made. Hence Particle filter can be used for both Gaussian and Non-Gaussian systems
- Does not involve any linearization techniques
- It uses random samples (particles) to represent the probability distribution

5. RESULTS AND DISCUSSION

The simulation study is carried out using the MATLAB software and the results obtained by applying a particle filter to a battery management system for estimating the states of a battery are analyzed.

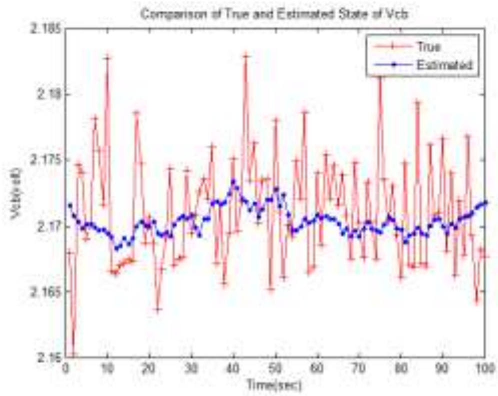

Fig. 3. Comparison of True and Estimated values of V_{cb}.

Fig. 3 shows that both the values of true and the estimated states tend to lie around 2.171V as the initial value of V_{cb} is chosen to be 2.171V. It can also be observed that the tracking of the filter is good as the estimates tracks the trajectory of the true state of V_{cb}.

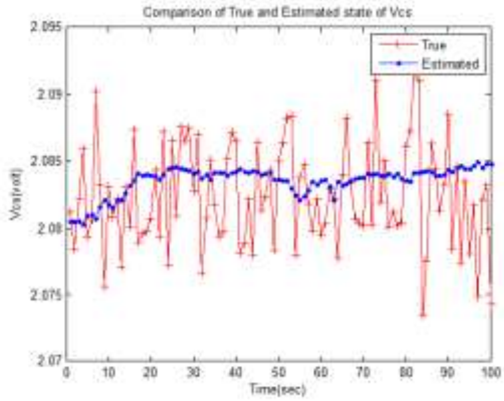

Fig. 4. Comparison of True and Estimated values of V_{cs}.

Fig. 4 shows the evolution of true and estimated states of V_{cs}. It is inferred that the estimate state tracks the true state with minimum estimation error.

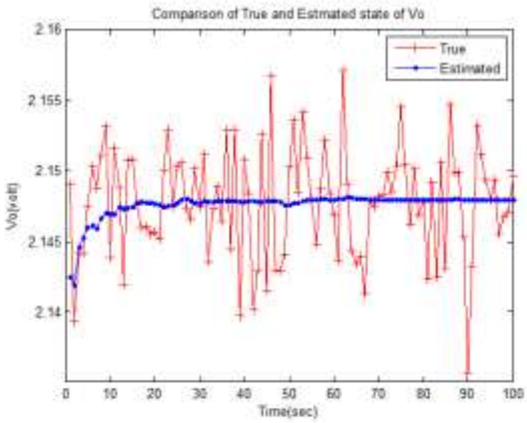

Fig. 5. Comparison of True and Estimated values of V_o.

During the implementation of the particle filter, the initial value of V_o is taken to be 2.148V which is the average of V_{cs} and V_{cb}. Fig. 5 shows the estimated state and it can be observed that the deviation of the estimated from the true value i.e., the estimation error is minimum. The estimation performance of a filter can be evaluated based on the estimation error values. An estimator is said to perform well if the error values (the difference between the true and the estimated values) converge towards zero.

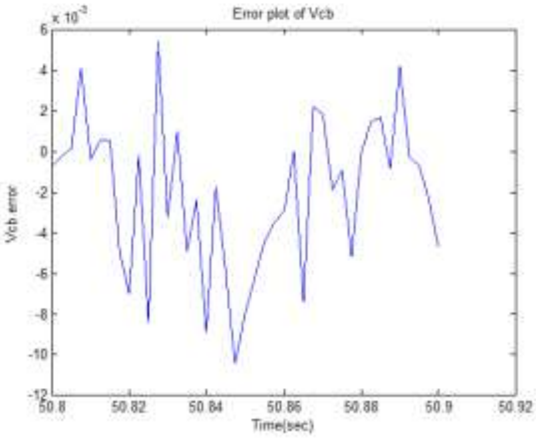

Fig. 6. Estimation error values of V_{cb}.

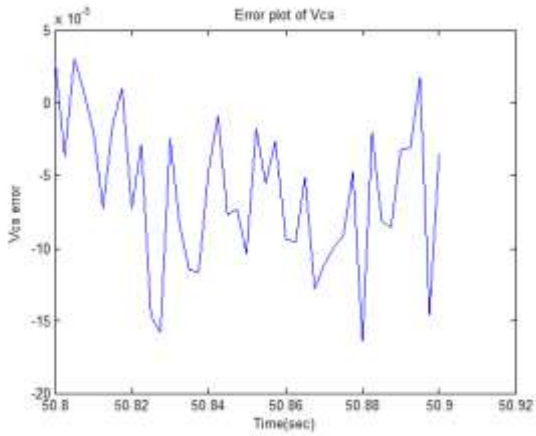

Fig. 7. Estimation error values of V_{cs}.

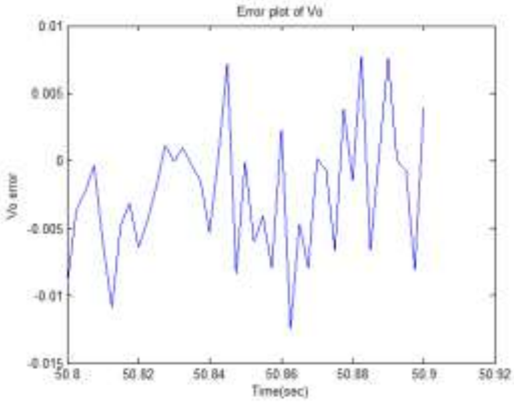

Fig. 8. Estimation error values of V_o.

The error plots of all the three states are shown in Fig.6 to Fig. 8. It can be observed that the value of the estimation error oscillates around zero. Due to the minimum estimation error, it can be inferred that the particle filter estimates the three states of a battery management system effectively.

Table 2
RMS error values of all the three states

Battery state	RMSE
V_{cb}	$4.1815\ e^{-004}$
V_{cs}	0.0085
V_o	$5.1471\ e^{-004}$

From the Table 2, it can be inferred that the Root Mean Square Error (RMSE) values of the estimated states obtained from particle filter is very minimum and hence it can be concluded that the estimation performance is good.

6. CONCLUSION

The study about the various state estimation techniques including the particle filter was carried out. The particle filter was then implemented to estimate the states of the battery as the battery management system is considered as the system of interest in this work. The simulation studies were carried out and the performance of the particle filter was analyzed. Based on the performance of the filter, it can be concluded that the particle filter estimates the states of the battery with very minimum estimation error.

7. REFERENCES

[1] Jingwen Wei, Guangzhong Dong, Zonghai Chen, " Model based fault diagnosis of Lithium Ion Battery using Strong Tracking Extended Kalman filter", Energy Procedia, Vol.158, pp.2500-2505, 2018.

[2] Arash Pake Talie, Wolfgang, "Electric vehicle Battery Management System using Powerline Communication Technique", Conference on Microelectronics and Electronics, Vol.51, pp.197-210, 2018.

[3] Xu Zhang, Yujie Wang, Duo Wang, Zonghai Chen, "An on-line estimation of battery pack parameters and state-of-charge using dual filters based on pack model", Energy, Vol.115, pp.219-229, 2016.

[4] Shen Yin, Xiangping Zhu, "Intelligent Particle Filter and Its Application on Fault Detection of Nonlinear System", IEEE Transactions on Industrial Electronics, Vol. 62, pp. 239-246, 2015.
[5] Xingtao Liu, Zonghai Chen, Chenbin Zhang, Ji Wu, "A novel temperature-compensated model for power Li-ion batteries with dual-particle-filter state of charge estimation", Applied Energy, Vol.123, pp. 263-272, 2014.
[6] Subrahmanyam, S.; Panicker, V. Microcontroller Based Self-Regulating Devices in Enclosed Environments. IARS' International Research Journal, v. 4, n. 1, 2014. DOI: 10.51611/iars.irj.v4i1.2014.35.
[7] T. O. Ting, Ka Lok Man, Nan Zhang, Chi-Un Lei, Chao Lu,"State-Space Battery Modeling for Smart Battery Management System", Proceedings of the International Multi-Conference of Engineers and Computer Scientists, Vol II,2014.
[8] M.Brandl, H.Gall, M.Wenger, V.Lorentz,"Batteries and battery management system of electric vehicles",Automation and Test in Europe Conference, Vol. 13, No. 6, 2012.
[9] B.S.Bhangu, P. Bentley, D. A. Stone, and C. M. Bingham, " Nonlinear Observers for Predicting State-of-Charge and State-of-Health of Lead-Acid Batteries for Hybrid-Electric Vehicles", IEEE Transactions On Vehicular Technology, Vol. 54, No. 3, May 2005.
[10] Chen, Morris, J&Martin, "Particle filtering for state and parameter estimation in batch process", Journal of Process Control, Vol.15, pp. 665-673, 2005.
[11] Arulampalam, M.S Maskell, S Gordon, "A tutorial on Particle filters for online non-linear/ Non-Gaussian Bayesian tracking", IEEE Transactions on signal processing, Vol. 50, No. 2, pp. 174-188, 2002.