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Electric Vehicle Battery's State of Charge Estimation Using Extended Kalman filter and Heuristic Search Algorithms

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***Abstract*— It is known that the State of Charge (SOC) of an electric vehicle's (EV) battery is the most essential parameter. It provides information about the battery's performance, allowing us to estimate the battery's charging and discharging capacities. Therefore, with an understanding of SOC characteristics, battery life, and EVs range can be enhanced. A variety of approaches to estimate the battery SOC % are presented in the literature, however, the filter-based method provides the most accurate results. This study provides an Extended Kalman Filter (EKF)-based SOC estimation coupled with other error-reduction strategies, including Particle Swarm Optimization (PSO), Genetic Algorithm (GA), and Battle Royale Optimization (BRO). The data used for this estimation is derived from the existing data model utilizing a Turnigy battery's LA92 drive cycle. It is observed that based on the given data set, the EKF provides an error percentage of 1.944% whereas, the proposed methodology of EKF with optimization technique especially PSO outperforms the EKF by attaining 1.8% error reducing the EKF SOC estimation error by 0.14%.**

Keywords*— *State of Charge, Lithium- ion battery, Extended Kalman Filter, Particle Swarm Optimization, Genetic Algorithm, Battle Royale Optimization technique.

I. INTRODUCTION (*HEADING 1*)

Presently, the car industry is undergoing a significant technological transformation from traditional automobiles to Electrified vehicles. When vehicles become electrified, there are numerous issues that must be solved in order to adapt to this change. Batteries are one of the essential components of Electric Vehicles (EV) that must be regularly monitored. Battery Management System (BMS) is responsible for computing State of Charge (SOC), State of Health (SOH), and Remaining Useful Life (RUL) and is used in EVs to monitor battery metrics such as current, voltage, and temperature. In addition, the BMS interfaces with onboard controllers and subsystems to maintain cell balancing, guarantee safe operations, and perform thermal management.

Due to the recent introduction of Battery Electric Vehicles (BEV) and Hybrid Electric Vehicles (HEV) to the market, it will take some time to evaluate their performance in real-world driving situations. The temperature and C- rate would reduce the accuracy of SOC estimation [1]. Consequently, the BMS should be adaptable to these changes in order to compensate for the performance loss that would impair the charging efficiency and the operation of the vehicle.

To operate at varied temperatures, power demands, and states, the BMS requires an accurate and highly efficient battery mathematical model as well as a robust estimating technique. This is challenging since the battery pack functions with dynamic discharging and charging currents depending on the driving style of the driver. For determining the SOC of a battery, accurate measurement of its chemical model and its cell characteristics is necessary. These parameters play an important role only for laboratory purposes and not for the real world [2]. In addition, the SOC is a quantity that cannot be measured or estimated directly, but it may be calculated using accessible characteristics like the voltage, current, and temperature.

Lithium-ion battery outperforms lead-acid and nickel-cadmium batteries in terms of power & energy density, self-discharge, operation cost, and reliability [3]–[6]. However, overcharging or discharging Lithium-Ion batteries can permanently destroy the battery cells, resulting in fire or explosion [7]. By preventing repeated charging and discharging, correct SOC estimation can extend battery life.

The estimation and controlling of SOC are important and can be useful for various applications in power system like Battery Energy Storage Systems (BESS), Uninterruptable Power Supply (UPS), and Electric Vehicles (EVs). Moreover, the accurate prediction of grid scale battery energy storage SOC also helps to enhance resiliency of the electrical grid during extreme events [8], [9]. However, there are various other parameters that affect the operation of BESS such as charging of EVs, penetration of distributed energy resources (Solar, wind, and other renewable energy resources), operating temperature, round trip efficiency, and other chemical considerations. For designing a BESS, it is essential to follow standard procedures like having a battery model that behaves similarly to a genuine battery and exhibits the same properties. The most commonly used type of battery models are the Electrochemical battery model and Equivalent Circuit Models (ECMs) [10]–[12], compared to ECMs electrochemical are more complicated as they involve mathematical equations to represent chemical reactions and battery deterioration [10], [13]–[16]. Whereas, ECMs use resistors, capacitors, and voltage sources for describing the electrochemical process and dynamics of the battery [17]. The ECMs model generally consists of the R_{int} model, Thevenin model (1^{st} order Resistor Capacitor circuit), Resistor Capacitor (RC) model, PNGV model, and enhanced Thevenin model (2^{nd} RC circuit).

Among the above mention ECMs, the 2^{nd} order RC ECM consists of a polarized capacitor for representing the transient behavior as shown in “Fig. 1.a”

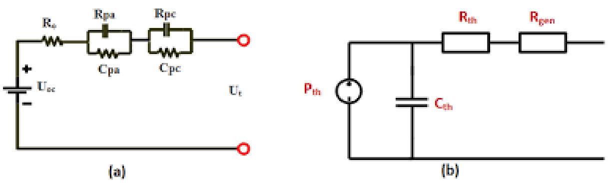

Fig. 1. (a) 2^{nd} order RC ECM [17] (b) thermal ECM [18]

For estimating SOC accurately, battery model must represent the statistical and dynamic reactions. If the accuracy of both the model increases, its computing time and cost also increases. Second-order RC ECM gives superior results as a tradeoff between model fidelity and computational accuracy. The battery's Open Circuit Voltage (OCV) serves as the driving force for second-order RC ECM. So, we want a reliable SOC estimation method to obtain a precise battery model. The SOC approximation technique is used to schedule the Battery Management System (BMS) accordingly, which controls the transfer of energy within a battery pack depending on cell voltages, temperature, SOC, and health. BMS plays a significant role in a battery by providing a risk-free working environment [19], [20]. Battery SOC computation is an important BMS function, but it is complicated by the battery's non-linear electrochemical process, making online estimation difficult [21].

The paper proposes a SOC estimation method using Kalman filter (KF), the filter is optimized using the Particle Swarm Optimization (PSO) technique to reduce the error percentage of the SOC further. The proposed technique is compared with the different optimization techniques like Genetic Algorithm (GA), Battle Royal Optimization (BRO) and the Extended Kalman Filter (EKF) based SOC estimation.

II. SOC Estimation Methods

The SOC of a battery is described as the battery’s current charge capacity Q(t) to it nominal capacity Q_n, which indicates the maximum amount of charge that can be stored in the battery [22].

$$SOC(t) = \frac{Q(t)}{Q(n)} \tag{1}$$

The accurate measurement of SOC reflects crucial aspects such as battery performance and remaining battery life [23], [24]. There are various techniques such as direct measurement, book keeping method, indirect measurement & hybrid method for accurate SOC estimation [25]. The direct measurement involves 3 sub methods: Open-Circuit-Voltage (OCV) method, terminal voltage method, and impedance method. The book keeping method involves coulomb counting and modified coulomb counting methods. The indirect measurement method involves the Kalman Filter (KF), Extended Kalman Filter (EKF), Fuzzy Logic, Unscented Kalman Filter (UKF) / Particle Filter (PF), Sigma Point Kalman Filter, Support Vector, and Neural Network. While hybrid method consists of combination of coulomb counting & Kalman Filter. This paper mainly focuses on EKF, PSO and Coulomb counting method discussed below in detail.

A. Coulomb Counting Method

The SOC of a battery is calculated using this technique, sometimes known as the Ampere-hour method [26]. The initial SOC approximation and battery current measurement determine the precision of this current sensor approach [27].

Due to high charging & discharging efficiency, long term monitoring needs of Lithium-ion batteries, the coulomb counting method is more practical for SOC approximation purpose. Apart from its inapplicability to SOC estimation in real-time, the method can be used to verify the precision of estimates obtained by other techniques.

$$SOC(t) = SOC_o - \frac{1}{C_{rated}} \int idt \tag{2}$$

Where,

SOC_o - Initial SOC value

i(t) - Current of the battery with a negative value at charge

C_{rated} - Rated capacity.

The initial SOC value (SOC) can be obtained by the OCV technique. The method discussed is simple to implement and is cheaper, however it has some downsides [28]. Considering Coulombic efficiency (ηAh) at various temperatures and charge rates would help in improving this method. It is the ratio of charges removed while discharging to charges entered during charging or the discharging capacity to charging capacity [29], [30]. This is given as:

$$\eta Ah = \frac{Qdischarge}{Qcharge} * 100\ \% \tag{3}$$

The modified coulomb counting equation is given as:

$$SOC(t) = SOCo - \frac{1}{C_a} \int \eta_{eq}\, idt \tag{4}$$

η_{eq} → Equivalent Coulombic Efficiency developed with charging and discharging coulomb efficiency

C_a → present available capacity

The Li-ion battery provides the highest coulomb efficiency in the SOC region when compared to different batteries, it exceeds 99%.

B. Kalman Filter

For estimating the hidden states of a linear system, the Kalman Filter (KF) is very effective. The KF method uses a combination of a recursive equation involving two phases. The first one is the prediction phase, in this phase several parameters like the system’s state, system output, and error are predicted. The second phase is the correction phase, based on the system's output value it corrects the current state of the system [31]. The process of the KF is illustrated in “Fig. 2”.

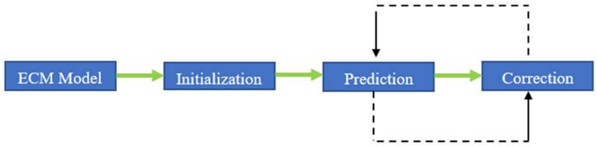

Fig. 2. Kalman filer process [32]

To determine the SOC using KF, a state-space model of the battery is created using the ECM. To estimate, there are two types of noise, the first of which is "System Noise" or "Model Uncertainty" (which could be due to temperature or weather conditions). Second is the equipment's "Measurement Noise." KF combines these two factors, minimizes them to the greatest extent possible, and provides us with the ideal state, therefore, resulting in achieving higher precision compared to others. The battery OCV and SOC have a non-linear relationship, therefore the KF is employable. For linearizing the relationship of SOC-OCV, a linearization technique can be used. The linearization process involves a discrete state space model, using the output equation and KF, the error is generated among the measurable quantity and system state variable is computed. Now for updating the system variables, the Kalman gain is utilized. Owing to the high nonlinear properties of the battery model, the KF approach may produce erroneous output. In this instance, the input is current, the output is the terminal voltage, and the SOC is placed in a concealed state [33]. Methods like KF, UKF / PF, and EKF could be utilized for approximating the hidden state of the system.

If the system is having high non-linear and non-Gaussian noise, and the error achieved is large, then Jacobian matrix is constructed in EKF [34]. EKF is an enhanced variant of KF utilized for calculating the internal variables of a dynamic system having nonlinear characteristic, using a state space model. It forecasts the system's forthcoming state built on past information [35]. The SOC is estimated using the advanced battery cell model, requiring a high computation capacity. It calls for two equations, the first equation involves the measurable input matrices, non-measurable noise, and system state matrices [36], [37]. The second equation depicts the output voltage concerning measurement noise, system state variable, and quantifiable input matrices. MATLAB is one of the software used for calculating the SOC. Sometimes, an inner filter in the EKF method is employed to vary the SOC, along with this an outer filter is utilized for altering the battery model parameters [38].

The inner filter proposes a voltage and measured current based on the SOC and model of the cell. By comparing measured voltage and the proposed voltage the SOC is adjusted. So, the system's output is SOC and its feedback is voltage. After keeping an eye on the current and voltage for a long time, the outer filter slowly changes the system model's parameters. This method finds and models cell ageing and other effects that happen over a cell's lifetime in real time. For achieving good results from EKF method, accurate modelling of the battery is required. Along with these requirements, it should be a dynamic system having nonlinear characteristics. Most common methods for estimating the SOC are Linear model, Thevenin model, Nernst Model, Unnewehr model and RC model [39].

C. Particles Swarm Optimization

This optimization technique is one of the bio-inspired algorithms, and it is a straightforward technique for searching the solution space for the optimal solution. This optimization technique differs from other optimization strategies in that it requires only one objective function and is independent of the objective function's gradient or any differential form. This algorithm is used to solve nonlinear and nonconvex optimization problems.

The PSO algorithm employs a collection of particles to search the space of an objective function for the ideal answer, known as the global best (gbest). At each iteration step, the PSO algorithm "moves" the particle swarm around the search space by altering the position and velocity of each particle, therefore attracting the particles to the point of the gbest. The PSO algorithm's flowchart is depicted in "Fig. 3" [40].

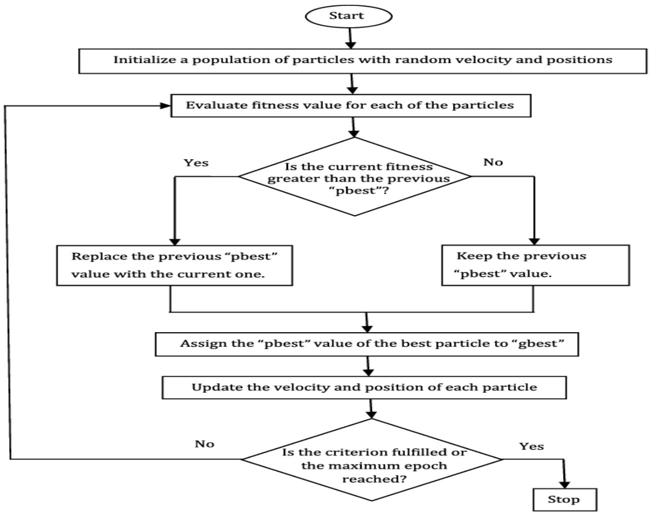

Fig. 3. PSO Algorithm

III. SOC ESTIMATION ALGORITHM

The 2nd order RC model mostly preferred for the battery modelling is shown in "Fig. 4"

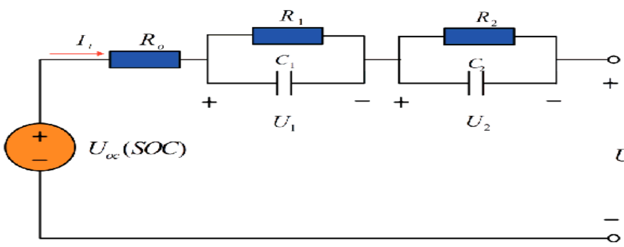

Fig. 4. 2nd order RC ECM Diagram.

The circuit is represented by battery's OCV, two parallel RC pairs, and internal resistance. These parameters are required to be improved, after improvement, the EKF generates a discrete-state-space-form. The EKF predicts the unknown system variables using the battery characteristics over time. The mathematical modelling and MATLAB code are taken from this reference, and the innovation of this study is that a PSO optimization technique is employed to optimize the parameters to further minimize the SOC error %. The battery modelling and EKF algorithm are described in detail below:

A. Battery Modelling

In "Fig. 4", V_{OC} denotes the OCV, E_t represents the output voltage of the battery, and R_0 represents battery's internal resistance. The SOC is denoted by Z_t. E_1 represents the first RC network's terminal voltage, while E_2 represents the voltage of second network. The Eq. (5) to Eq. (8) represent the dynamics of the ECM in state space.

$$Z(k+1) = Z(k) - \frac{\eta \Delta t \, i(k)}{Cn} \quad (5)$$

$$E_t\ (k) = V_{oc}\,(k) - E_1\,(k) - E(\text{k})\text{- i(k)Ro} \quad (6)$$

$$E_1(k+1) = e^{\frac{-\Delta t}{R1C1}} E_1\,(\text{k}) + R_1\left(1 - e^{\frac{-\Delta t}{R1C1}}\right) i(k) \quad (7)$$

$$E_2(k+1) = e^{\frac{-\Delta t}{R2C2}} E_2\,(\text{k}) + R_2\left(1 - e^{\frac{-\Delta t}{R2C2}}\right) i(k) \quad (8)$$

Current i(k) is the input to the model at step time k. Δt is the sampling time in seconds, R_1, C_1, R_2 and C_2 are the model parameters. While V_{OC} is computed as a function of SOC and temperature in Eq. (9).

$$V_{OC} = \text{f(Z, Temperature)} \quad (9)$$

The states and the measurement equations are calculated in Eq. (10) and Eq. (11) as follows:

$$X_{(k+1)} = A_k X_k + B_k U_k \quad (10)$$

$$Z_{(k)} = C_k X_k + D_k U_k \quad (11)$$

Where,

$X_{(k+1)}$ → System state vector (at time = k+1)

x = Z, E_1, E_2 → State variables

$U_k = i_k$ → System input

$O_k = V_t$ → System output

Eq. (12) to Eq. (15) represent the A, B, C, D matrices given below:

$$A = \begin{bmatrix} 1 & 0 & 0 \\ 0 & e^{\frac{-\Delta t}{R1C1}} & 0 \\ 0 & 0 & e^{\frac{-\Delta t}{R2C2}} \end{bmatrix} \quad (12)$$

$$B = \begin{bmatrix} \frac{-\Delta t}{Q} n[k] \\ R_1\left(1 - e^{\frac{-\Delta t}{R1C1}}\right) \\ R_2\left(1 - e^{\frac{-\Delta t}{R2C2}}\right) \end{bmatrix} \quad (13)$$

$$C = \begin{bmatrix} \frac{\partial V_{OC}}{\partial Z} & \frac{\partial V}{\partial E_1} & \frac{\partial V}{\partial E_2} \end{bmatrix} = \begin{bmatrix} \frac{\partial V_{OC}}{\partial Z} & -1 & -1 \end{bmatrix} \quad (14)$$

$$D = -R_0 \quad (15)$$

B. Extended Kalman Filter

A non-linear system's states are estimated using the EKF, which uses a two-step prediction-correction algorithm as described in Eq. (16) through Eq. (20). In these equations:

k → discrete time point,

K → Kalman Gain,

P → covariance of measurement error,

Q → covariance of Process, and

R → covariance of output

The updated measurement is carried out after the prediction or time update. Up till all the data has been processed, this cycle is repeated. A variable's estimate is indicated by the nota bene symbol, where |k denotes a predicted or a-priori estimate and |k + 1 denotes an updated or a-posteriori estimate.

Estimation:

1. Projection of the upcoming states (a-priori):

$$\hat{X}_{k+1|k} = A\hat{X}_{k|k} + Bu_k \quad (16)$$

2. Projection of upcoming error covariance:

$$P_{k+1|k} = AP_{k|k}\square\square + Q_k \quad (17)$$

Rectification:

1. Calculation of Kalman gain:

$$K_{k+1} = P_{k+1|k}C^T(CP_{k+1|k}C^T + R_{k+1})^{-1} \quad (18)$$

2. Estimate upgradation using measurement zk (a-posteriori):

$$\hat{X}_{k+1|k+1} = \hat{X}_{k+1|k} + K_{k+1}(Z_{k+1} - C\hat{X}_{k+1|k}) \quad (19)$$

3. Upgradation of error covariance:

$$P_{k+1|k+1} = (1 - K_{k+1}C)\, P_{k+1|k} \quad (20)$$

Gaussian distribution is the main base for EKF method; therefore, it is necessary to linearize the states specified in Eq. (16) through Eq. (20) for appropriate functioning of the method. C is the lone matrix that entails linearization, as the relationship between SOC and OCV is nonlinear [41].

C. Parameters tuned by Optimization Technique

For optimizing the battery parameters (i.e., R_0, R_1,R_2,C_1,C_2), various methods such as PSO, GA, and BRO are utilized. Using the provided data, the limits of these parameters are determined. Random initial values for battery parameters are chosen. The EKF main file is considered as the objective function, for estimating the SOC of the battery via EKF method. In this method, the parameters' optimal values are determined through optimization so that the SOC error is minimized. These numbers are then employed by the EKF algorithm to calculate the state matrices, followed by the prediction and corrective update.

IV. Result & Discussion

The battery parameters (i.e., R_0, R_1, R_2, C_1, C_2) are optimized using PSO. The optimized values of these parameters are used for calculating the state matrices as mentioned above. The Kalman Filter utilizes a two-step prediction & correction update as shown above. The P (measurement error covariance), Q (process covariance) and R (output covariance) matrices are obtained. This procedure keeps on repeating until the all the data is processed. The SOC error and the terminal voltage error are calculated. The results obtained from the PSO are compared with BRO, GA, and the EKF SOC estimation algorithm. The error obtained from PSO is less compared to other algorithms. The Root-Mean-Square-Error (RMSE) error for both terminal voltage and SOC are matched with different techniques as shown in "Table I".

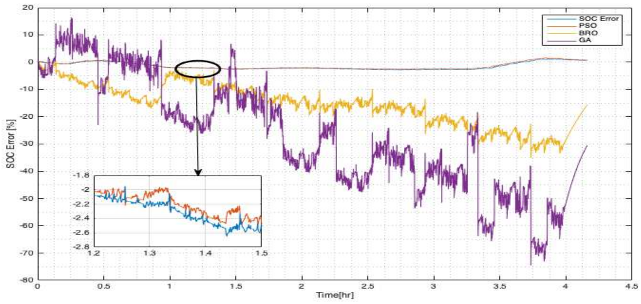

Fig. 5. SOC Error Comparison

TABLE I. COMPARASION OF RMSE OF DIFFERENT ALGORITHMS

Algorithms	Terminal Voltage Error % (RMSE)	SOC Error % (RMSE)	Maximum Terminal Voltage %
PSO	**1.0714**	**1.8073**	**13.4439**
BRO	22.8352	17.3346	266.8244
GA	136.9381	33.9531	$1.3370*10^4$
EKF	1.3154	1.9440	17.7890

As depicted in “Fig. 5”, the SOC error achieved by techniques such as PSO, BRO, GA, and EKF SOC estimation. It has been found that PSO and EKF estimation approaches produce less inaccuracy than BRO and GA. The RMSE for BRO is approximately 17.33%, whereas the error for GA is close to 34%. This demonstrates that these two strategies are ineffective for SOC estimation. Nonetheless, the PSO method lowers the inaccuracy produced by EKF Estimation. The RMSE of the EKF SOC is over 2%, while the PSO error is approximately 1.8%. “Fig. 6” depicts the error between the PSO and EKF SOC estimation methods in greater detail. It is concluded that PSO outperforms other optimization strategies.

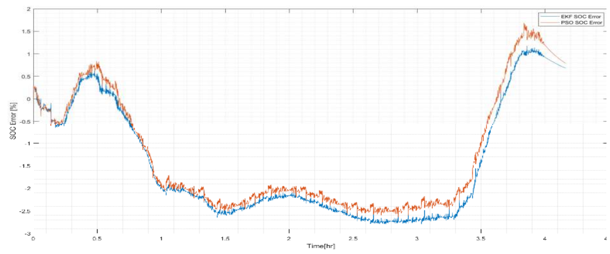

Fig. 6. SOC Error Comparison of EKF and PSO

V. CONCLUSION

In this paper, optimization of second-order RC ECM parameters like (R_0, R_1, R_2, C_1, and C_2) is achieved using several optimization techniques like Particles Swarm Optimization (PSO), Genetic Algorithm (GA), and Battle Royal Optimization (BRO). The State of Charge (SOC) is calculated for these optimization techniques and is compared with the Extended Kalman Filter (EKF) SOC estimation method. It is observed that through the EKF SOC method, the SOC error was 1.94 % and through PSO the SOC error obtained was 1.80 %. Later, the error from PSO is compared with two different optimization techniques like GA which is the oldest technique, and BRO the latest optimization technique. The error obtained from PSO is less compared to GA and BRO i.e., 33.95% and 17.33 %. The results show that PSO provide better SOC estimation compared to existing EKF and other optimization techniques used.

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