Real-Time Electric Vehicle Battery SOC Estimation Using Advanced Optimization Filtering Techniques

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Abstract

Improving the Extended Kalman Filter's (EKF) State of Charge (SOC) prediction for EV battery packs is the primary goal of this section. Optimised batteries management procedures rely on SOC estimate that is both accurate and reliable. The EKF is a popular tool for estimating nonlinear states, but how well it works relies heavily on which noise coefficient matrices are used (Q and R). Experimental testing and other conventional approaches of calibrating these matrix systems are extremely costly and time-consuming. In order to tackle this, the section delves into the integration of four state-of-the-art metaheuristic optimisation methods: GA, PSO, SFO, and HHO. By minimising the mean square error (MSE) among the real and expected SOC, these techniques optimise the Q and R matrices. When looking at preciseness, converging speed, and resilience, SFO-EKF comes out on top in both static and dynamic comparisons. By greatly improving the reliability of SOC estimations, the numerical results show that SFO-EKF obtains the lowest MSE & RMSE. This study advances electric car batteries by providing a realistic scheme for combining optimisation methods with EKF to offer highly effective and exact SOC estimates. When as opposed to TR-EKF, GA-EKF, PSO-EKF, and HHO-EKF, the SFO-EKF approach shows the best accuracy, with an improvement of over 94%. This is a result of the suggested model's exceptional efficiency in SOC estimates.

Keywords: SFO-EKF; EKF, GA-EKF; MSE; PSO-EKF; HHO-EKF

1. Introduction

Electric vehicles (EVs) are an essential component in the process of resolving the ecological problems that are plaguing the globe today. The vast majority advanced as well as developing nations have incorporated EVs into their regulations in order to reduce carbon footprints and provide affordable cars with no emissions [1-2]. This is due to a number of factors, including changing climates, advancements in clean energy, batteries, rapid urbanisation, collecting information and evaluation, and security of electricity. Batteries electric vehicles (BEVs), which are completely operated by their batteries and replenished by the motorbike that plugs it in, provide an easy fix to this problem. The lithium-ion batteries are the most suitable for electric cars amongst the several kinds of batteries that are now available on marketplaces. This is because of the numerous benefits that those batteries provide, including a significant amount of energy, minimal upkeep requirements, and a long service life. Li-ion batteries, although their many benefits are exceptionally susceptible to both overcharging and deep discharging, both of which may shorten their lifetime and potentially result in a collapse or fire. According to the author, the power supply must be used in a Safe Operating Area (SOA) in order to fulfil its intended purpose. At the same time, it is necessary to have a Battery Management System (BMS) in order to ensure that the steps of charging and

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discharging are carried out in a secure manner. The BMS is comprised of a few operational components that are almost entirely separated into two categories: both hardware and software [3-4]. As can be seen in Figure 1, the BMS elements are broken down into their separate elements. The software is the most important component of the whole thing since it is responsible for controlling all of the hardware's activities and analysing sensory information in order to arrive at choices. By handling information online, a significant number of errors will be identified and corrected. A complex data evaluation is necessary in order to provide alerts about malfunctioning batteries. When it comes to revealing the pre-alarm when the issue occurs, data collecting is of more importance.

The application's commands are followed by the physical parts in order for them to carry out their functions. Utilising sensors allows for the accurate monitoring of both the current state and temperature of the batteries. Monitoring and analysing the behaviour of a battery, locating defects, and preventing batteries from overheating are all tasks that need a reliable batteries model. In addition, the SOC performs a significant part in the function of the batteries, and as a result, it is essential that it remain tracked utilising the appropriate estimate techniques [5]. A appropriate optimisation technique is being performed in order to optimise the powering sequence for a pack of batteries after the behaviours of the battery itself have been evaluated and analysed. It is essential for battery management systems to include an outlet for charging given that it has a direct influence on the availability and safeguarding of batteries. The battery is protected from harm, temperature swings are kept to a minimum, and the effectiveness with which energy is converted is improved by a recharging method that has been thoughtfully executed [6]. Next, a data gathering system may be used to save all of the settings that are associated with a pack of batteries. Finally, the controller part of the network determines whether the data that has been saved is within the safe functioning limitations of the battery's capacity. The electrical device will be protected from harm by a security mechanism in the event that any unexpected circumstance arises during the procedure of operationalizing the energy source. The BMS and the power source are connected via an operator interaction that is provided by an effective communication system.

One of the most challenging aspects of designing a high-capacity system is the identification of faults. Because of the irregularity of the battery cells, a major electric vehicle accident occurred. Deficiencies in the cells of a battery are brought about by the fact that the up-to-date temperatures, impose, and discharging all surpass the limit worth [7-8]. Problems have the potential to create fires and harm to batteries because of the bursting of the cell. In order to avoid cell discrepancy, it is essential to have a valid charge technique as well as a circuit that balances the cells.

The majority of balanced cell circuits are constructed simply on a foundation of voltages. Although these devices are regarded to be fairly straightforward, they ultimately result in terrible performances. active cell equilibrium is developed for the purpose of improving efficiency. This is centred on a standard SOC. In spite of the fact that the cell balanced method that depends on SOC and voltages is necessary for fault identification, it is vital to estimate the SOC of one cells prior implementing the cell's balanced approach [9]. The state of charge therefore functions as a factor for the purposes of power computation, cell balance, and defect diagnostics. The calculation of range for driving, cells balance, electrical consumption, control of energy, thermal handling, security controls, and remaining usable life projection of an electric vehicle batteries are all dependent on each condition. SOC is the key variable needed that determines and regulates different states in the majority of the research that have been conducted for the purpose of estimating the SOC of the cell within a battery. This is due to the fact that SOC is positively connected with additional states. The figure 1 depicts the BMS's software and hardware elements.

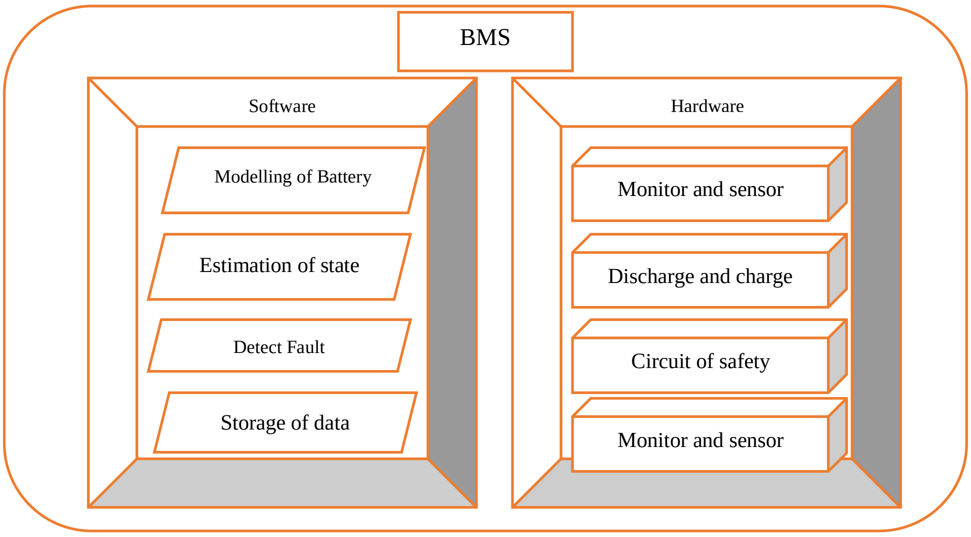

Figure 1. Depiction of BMS's software and hardware elements

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In addition, the State of Health (SOH) is gradually shifting because of capability fade, temperatures, inner resistance, and condition of charge SOC [10]. The electrical charging technique, heat transmission, and physicochemical characteristics of the battery's cells all contribute to the variation of the State of Temperature (SOT) on a scale that is moderate. State of Energy (SOE) and State of Power (SOP) are both subject to rapid change; nevertheless, they are largely dependent on SOC. Consequently, the estimate of SOC is necessary for the assessment of other states. The SOC is an indication that regulates both charge and discharge limitations for the most secure utilisation of battery. Furthermore, the most significant issue encountered with electric vehicles is range anxiety, which refers to the dread feeling of being out of energy [11].

This issue is made worse by the fact that the accessibility of SOC is erroneous. As a result of the rigors requirements for operation that are present in electric vehicle programmes, it is challenging to get an accurate state of charge from only both voltage and current that are monitored [12-14]. In light of this, the estimate of the SOC is a comprehensive solution that helps to maintain an electrical device between the required working limits and reduces the rate at which it fails due to charging too much and overloading. In spite of the fact that a variety of estimating techniques are utilised, model-based methodologies for estimation are now recognised as the technology of choice. Consequently, the first step is to create an illustration of the batteries, but the preciseness of the replica has a direct impact on the assessment of the condition. In order to precisely calculate the SOC of a battery, it is necessary to have a battery simulation that has been adequately taught in addition to a method that is suitable for estimating SOC. Therefore, in order to develop a BMS, it is essential to determine the appropriate batteries architecture and SOC estimate approach. This is because both of these factors are interdependent on one another. For the purpose of monitoring and analysing the behaviour of the batteries, locating defects, and preventing batteries from melting down, a complete battery structure is necessary. For presenting the behaviour of the batteries, typical modelling and the variables that are linked with the models are investigated and explained. In light of this, Electrochemical Models (EMs) and Equivalent Circuit Models (ECMs) are implemented extensively for designing model-based SOC estimate methodologies [15]. Although EMs tend to be more precise than ECMs, but fail to deliver a suitable balance among the extensive nature of the model and its high level of accuracy. ECMs are generally accepted frameworks for real-time BMS tasks such as state estimating, cell equalisation, and charge management and optimisation. This is because EMs need sophisticated conceptualisation and application. It has been shown that the Two RC-ECM model is suitable for use in internet-based applications because to its advantageous characteristics, which include high precision, straightforwardness, and great modelling needs. SOC is responsible for updating variable in time variables at each phase of the process. This is because the model parameters are highly reliant on SOC. The characteristics of the simulation are being determined online or offline with the purpose of developing an online SOC estimate.

The majority of researchers choose online recognition approaches because they provide a reduction in the cost of computing and the amount of time required to perform the recognition procedure for digital SOC estimate. However, the features of the simulation need to be determined live in order to improve the precision in the models-based SOC estimate approach for scenarios that include real-time electric vehicles. In light of this, the VFFRLS methodology is put into action in order figure out the parameters related to the model for batteries for the purpose of SOC estimate [16]. If one wants to develop a system to manage batteries BMS, it is essential to choose the appropriate charge architecture and SOC estimate approach from the outset. This is because both of these factors are interdependent. The Kalman Filter (KF) family algorithm is superior to Artificial Neural Network (ANN) algorithms when it comes to the estimate of SOC [17]. This is because of the KF group method's self-rectifying capability, converging rate, durability, and correctness. For estimating the SOC of a battery, it is required to first develop a state-space simulation of the storage device when using a KF-based technique. It takes state of charge into consideration as an operational parameter and establishes a correlation between SOC and measurements like voltages and power. Considering that batteries is a system that is nonlinear, the enlarged version of KF shows a great deal of promise for the estimate of the SOC. Despite the fact that the Unscented Kalman Filter (UKF) and the Particle Filter (PF) have been created and provide satisfactory outcomes for SOC estimating, the EKF is chosen owing to the fact that it offers a balance among precision as well as. Mainly because other sophisticated, filters not only enhance accuracy yet additionally improve the level of complexity of the calculation. It is essential to have a procedure that is precise while not being too difficult in order to adequately handle the demanding working circumstances of an EV.

2. Related Work Done

With the use of mathematical equations, electrolytic equations are utilised to provide a description of the behaviours of batteries. These behaviours are dependent on the fluid's quantity, the size of each electrode (the anodes and the anode), also the chemical reaction that occurs within the battery itself. In spite of the fact that EM is capable of providing precise batteries data, it requires a greater amount of processing time and energy in order to discover a multitude of characteristics. These variables include electrolytes prospective, solid prospective, open-circuit prospective, potential, liquid quantity, solids quantity, cell voltage, up-to-date temperatures, and many more. In addition to this, it is challenging to incorporate in systems that operate in real time.

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It provides a summary of the analysis of and comparisons between the many kinds of chemical theories of batteries. The author on a foundation of the chemical procedure that involved it proposed an electrochemical framework known as the Pseudo-2-D (P2D) concept. Because of the large number of complex formulas, the P2D model requires a significant amount of time to simulate, which renders it computationally expensive for implementation in BMS scenarios [18]. The researcher suggested an improved order electromagnetic model (EM) that takes into account the typical amount of liquid electrolyte rather than its placement between the conductive surfaces. Additionally, the model is capable of being applied in actual time aboard buses, despite the fact that it loses certain data. The process of determining the criteria, on the other hand, is quite challenging [19]. The battery's characteristics have been determined by the investigator via the use of an algorithm based on evolution and a projected state of charge. For the purpose of verification, the model is executed repeatedly and a sample size of one thousand is used. Additionally, the detection of eighteen variables is completed in a span of six hours. The precision of this simulation is diminished because of certain assertions that are included with the goal to lower the precision of the prediction.

However, this approach does have the benefit of decreasing the amount of processing power required in comparison to the entirety of the approach. The author suggested an approximation theory that controls the method of diffusion as well as the movement of the electrolytes inside the battery's cells. The investigator [20] has suggested a reduced-order framework that depends on a singular fluctuation technique and an averages theory. This model is meant to calculate the SOC of Li-ion batteries and to forecast the capacity of the pack of batteries to discharge and discharge. The approach of design reduction that is being discussed here is appropriate for all batteries. The development of a high-fidelity simulation that takes into account humidity, ageing, and ability fade, on the other hand, not only enhances the degree of precision but also additionally enhances the degree of detail.

Electronic control modules (ECM) make use of various electrical gadgets, including capacitors, resistance, and source of voltage, in order to explain the wiring behaviour of the batteries. In accordance with the principles of circuit analysis, the formulae and variables for the structure. When it comes to ECM, an extremely high-rated capacitors or a regulated voltage denotes the Open Circuit Voltage (OCV) of an electrical device. This voltage is the most essential variable for a variety of estimation of states methodologies [21]. A comparative study about twelve alternatives for twelve ECM examples was conducted by the researcher estimated six different battery designs, including a combination framework, a straightforward framework, a zero-state fluctuation model, a one-state oscillations framework, and a better rectifying themselves emulate (with a two-state Lower Pass Filter Assembly and a four-state Low Pass Filter). The Rint model is the most basic example of an ECM. This model looks at the pack of batteries as an input to voltage involving parallel resistance. The features of the power source that is used in electric vehicles cannot be adequately presented by this method, despite the fact that it is easy to apply. According to the authot, the Rint model is modified by the addition of only one Resistance-Capacitance parallelism networks to create a Thevenin version.

It is common practice for utilising the Thevenin framework in order to accurately represent the dynamic features of batteries. The revised edition of the Thevenin concept is a Partnership for a Newer Generations of Vehicle (PNGV) version [22]. The framework incorporates a fictive capacitor in order to capture the impacts of OCV fluctuation. Open circuit's voltages, electromagnetic opposition, fictive capacitors, polarisation obstruction, and capacitance are the components that make up the PNGV method, which is also referred to as the FreedomCar model. According to the investigator, the PNGV model makes an excellent option for regions with a low SOC, even if it is not appropriate for regions with a high SOC. Resistance-Capacitance (RC) network-based algorithms are among the many ECM predicts that are accessible in the literature. They include examples that consist of one RC network ECM, two RC network, or three RC system ECM.

These designs have become popular over use in websites and apps, two of these three RC network models have a high level of accuracy when it comes to predicting how they affect the current entered and the resulting voltage (I-V) for a battery, along with the amount of time required for the pack of batteries to have its charge and discharge. Because batteries are a nonlinear structure, the motions of the batteries change depending on the operational circumstances, which include the SOC, temperatures, charge rate, and discharge rates of a batteries [23]. Because of this, the simulation guaranteed the data. Because of this, the battery design is unchangeable, and the specifications of the design need to be determined. In order to determine the variables of the framework based on the results of experiments, the popular Least Square (LS) and the Genetic Approach are used. The researcher demonstrated that the template has to be recognised. In the process of developing the BMS, the rendering is discovered using real-time operational data from EV eliminating the need for testing in the lab. Real-time cell properties may be captured and updated with the use of an autonomous actual time batteries characterizer that was successfully created. A representative sample of the RC model that was produced at the National Renewable Energy Laboratory (NREL) was recently obtained for the purpose of assessment [24].

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It is possible to get data in real time by using the Advanced Vehicle Simulator (ADVISOR) programme. Furthermore, the verification of the framework, the level of convergence of the estimating method, any error in the proof of identity, and the elimination of the bias are all subjected to a comprehensive verification process. On the other hand, the components of the ECM circuitry do not adequately explain the correct appearance of cells. In addition, the variables of the simulation are continually revised taking into account the SOC, temperatures, and fill-discharge frequency of a battery. It is true that DDM is substantially more effective than ECM and EM, but the degree of effectiveness is strongly dependent on the quantity of information as well as the learning technique. DDM is capable of approximating non-linear charge properties thanks to its mathematical capabilities. A number of can describe the behaviour of batteries driven by data designs, such as ANN, Adaptive Neuro-Fuzzy Inference Systems (ANFIS), Deep Neural Networks (DNN), and Support Vector Machines (SVM) [25].

ANN is a strong tool that may be used to construct a framework for any kind of non-linear functional. This is if the training of the data is carried out correctly. A substantial amount of accurate information with a variety of load circumstances, as well as a substantial amount of instruction time, are required for this algorithm to achieve its desired level of accuracy. When compared to other driven by data simulations, the Feed Forward Neural Network (FFNN) is most simple because it has a straightforward procedure for learning and does not need a lot of computing. Similar to FFNN, DNN is characterised by a high level of processing speed in comparison with different learning engines. FFNN and DNN, on the other hand, are one-way networks that do not take into account the past usage of the information being analysed.

Throughout the process of online SOC estimating, there is no requirement for a backwards pass since both are adequately trained. This means that networks biased and weighting are learnt via offsite operations. As a result, the most significant obstacle to overcome is that the models need to be learned accurately in offline environments. The authors of have said that the amount of time necessary to construct a deep neural network (DNN) may range anywhere between just a few days to forty to fifty hours, depending on the outside temperature. This is despite the fact that learning is carried out on the Graphical Processing Unit (GPU), which offers the beneficial feature of parallelism. For determining the necessary voltage of the battery, the Nonlinear Auto Regressive model with eXogenous input (NARX) is used in the study conducted by the author.

The Recurrent Neural Network (RNN) has the benefit of utilising historical records of data along with recurring the facilities, which is not the case with the ANN. The sole issue is losing memory, which indicates that it is unable to record that data for an extended period due to the occurrence of gradients disappearing. For this reason, the Gated Recurrent Unit (GRU)-Recurrent Neural Network and the Long Short-Term Memory (LSTM)-Recurrent Neural have been developed in order to capture the needs for the long term. Because of the fact that GRU-RNN is organised across time, it is necessary to use an additional back propagation technique, which is referred to as Back-Through-Time Propagation (BPTT), in order to construct a network. For enhancing the GRU-RNN process of training and increasing the degree of convergence rate, it is vital to do data normalisation in the appropriate manner. LSTM involves the addition of an area of memory to an already hiding unit in order to retain the data for a greater amount of time. According to the investigator, ANFIS has a combination of benefits, including the adaptability of fuzzier structures, the variability of fuzz structures, and the training potential of neural networks as well. To accommodate the chaotic behaviour of the batteries, the Takagi Sugeno (T-S) fuzzy contains an intrinsic multiple-model architecture. This framework allows the simulation to function properly. However, it is primarily rule-driven, and the precision of the predicted outcome fluctuates with the total number of rules. On the other hand, black box models may offer proper outcomes, though they need greater computing intricacy, and it is difficult to analyse this kind of models because of its black box character.

3. Objective of the research work

The optimisation of the EKF variables is the major goal of the research work that is being done on the SFO-EKF models. This is done with the intention of improving the precision and efficacy of the SOC estimate for batteries in electric cars. The conventional trial-and-error approach for picking noisy covariance matrix variables (Q and R) is a key factor that has a substantial influence on EKF effectiveness. The purpose of this research is to solve the issues that this strategy presents. The study endeavours to minimise the mean squared error (MSE) among the real and predicted SOC by using the Sunflower Optimisation (SFO) method. This will ensure that the reliability of estimation is enhanced throughout the process. A strategy that is both resilient and efficient in computing is provided by the SFO method, which is used because of its capacity to effectively locate global optimums despite becoming ensnared in local responses.

4. Motivation for the research work

The vital requirement to improve the precision and efficacy of SOC) estimation for battery packs for electrical vehicles was the impetus for the development of the SFO-EKF system. This is a significant aspect in enhancing battery safety and lifetime, and it was the driving force behind the development of the framework. Traditional EKF algorithms experience a decline in accuracy because of the improper decision to use stochastic covariance matrix

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sizes (Q and R), these frequently get tweaked by procedures that involve trial and error. These approaches are not only lengthy but also inconsistent, and they do not guarantee optimal effectiveness across a wide range of different operational situations. Despite the fact that well-established optimisation strategies such as GA, PSO, and HHO are currently used to enhance EKF tuning, these strategies often suffer with concerns pertaining to closure velocity, computing complexities, or local optimality. Simulating the effective and nature-inspired migration of sunflower approaching the sun, the SFO approach presents a potential solution because to its straightforwardness, durability, and the capacity to steer clear of local maxima.

5. The proposed Method

A wide variety of types of batteries for the establishment of the battery management system (BMS) has been offered because of the progress that has been made in the battery industry. Within the framework of model-based estimate of SOC methodologies, model batteries are often stated as phase equations. For the purpose of this chapter, the ECM that is usually employed will be utilised since it accurately portrays the multiple changing features that the battery has. Consequently, the ECM had been utilised in an appropriate manner in order to develop the model-based SOC estimate technique. When using the modelling-based SOC estimate technique, the reliability of the estimating is heavily dependent on the battery's models and the estimating method. The fusion technique may be thought of as a more general term for these methods. Because of the fact that the settings of the framework are time-dependent, it is necessary to identify the variables often at each time step. Consequently, the VFFRLS approach is used in order to carry out the simulation variable verification, and the EKF technique is utilised in order to calculate the current condition of the batteries. Calculating the cell voltages and comparing it to the measuring result is the fundamental premise behind the estimate of the state of charge (SOC) using EKF. It is possible to make use of a Kalman gain matrices in order to rectify the voltage fluctuation was sent again to the battery structure in order to assess the state of charge of the batteries.

$$Y_L = BY_{L-1} + CV \qquad (1)$$

$$X_L = DY_L + EV \qquad (2)$$

Given that, there is a single variable for input and state parameters Y, B, C, D, E the resultant matrix is an odd number. Figure 2 details the EKF technique and the matrix structure involved.

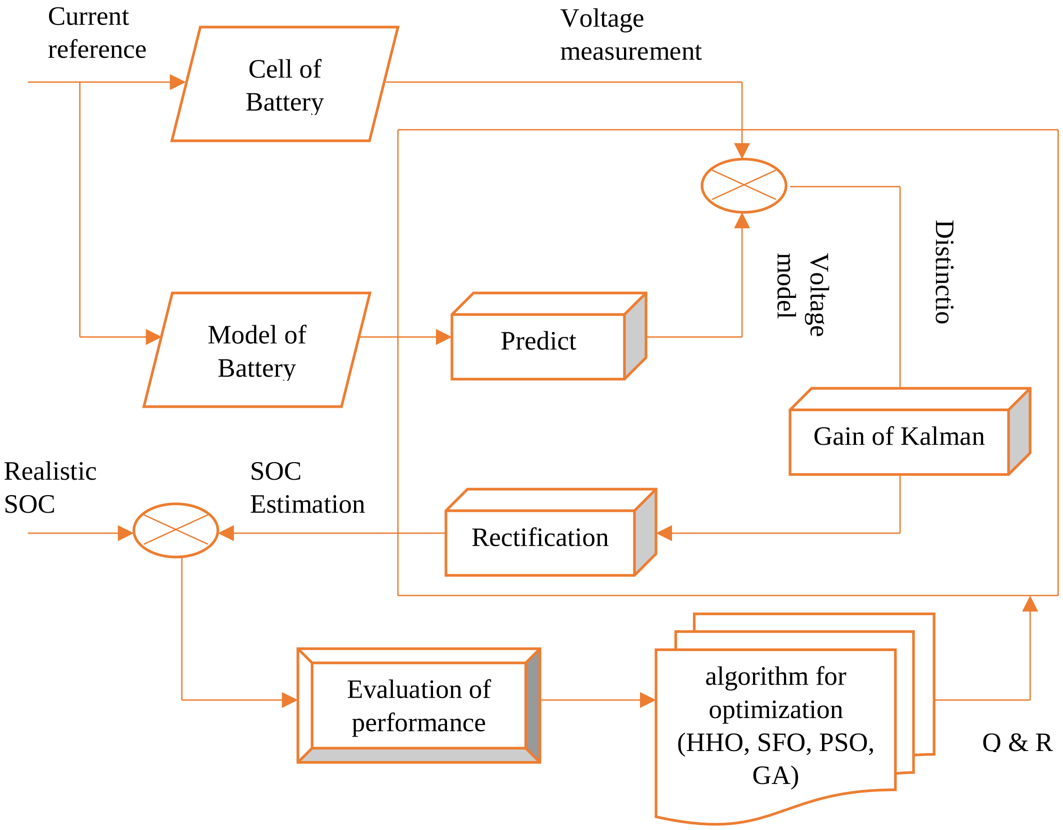

Figure 2. Architecture of suggested approach

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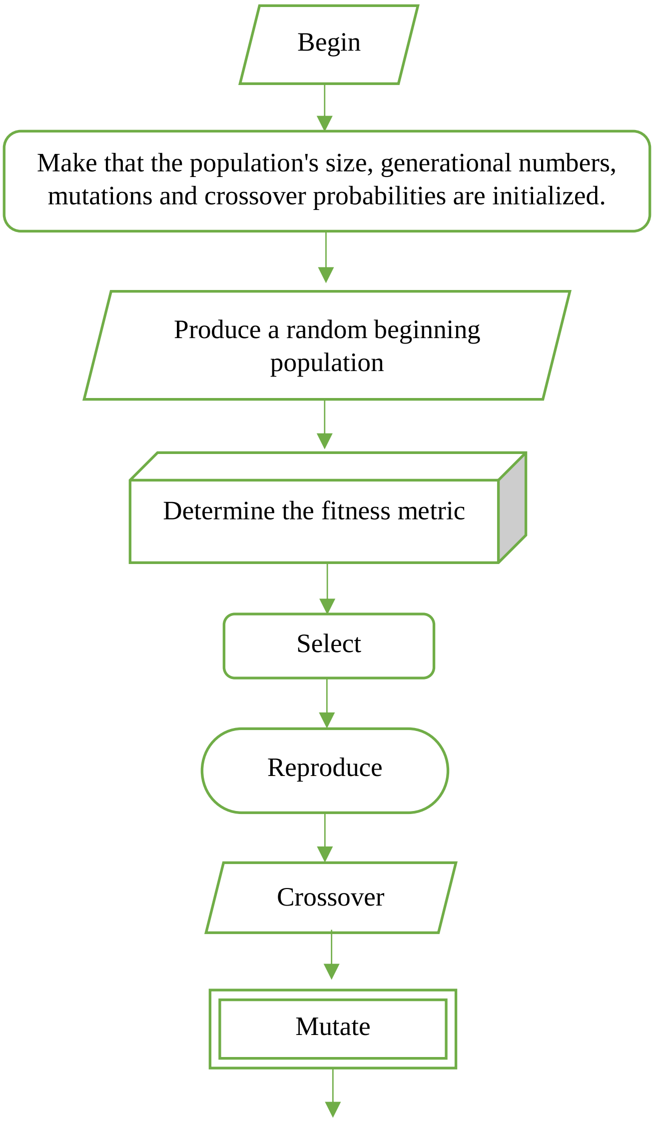
The value ranges of the noisy coefficient matrices are crucial to the EKF approach. When it comes to accurate faults, choosing the right noise coefficients is just as important as choosing the right batteries modelling type and filtration procedure. Typically, an iterative process of trial and error, or adaptable update at each step, both of which add computing weight, determines the noisy matrix covariance Q and R. Noise correlations matrix structures, which significantly affect the current state of EKF charges estimations, are found in this study utilizing an optimization approach. The optimization method receives as a measure of fitness a measurement of the MSE across the real and projected SOC, as shown in Figure 2. Prior to estimating SOC online, the optimization technique determines Q and R matrix separately. The use of metaheuristic algorithms (MA) has grown substantially in recent years, and these techniques have found applications in many different domains. A plethora of novel MAs have been advanced in the last few years. When dealing with optimization issues of this complexity, the MA is a useful tool. This method falls under the category of cybernetic approximations. Scientifically, MAs have come a long way in recent years. The academic field is replete with methods that take their cues from the natural world. This tuning procedure makes use of both classic and new methods, such as MAs GA, PSO, HHO, and SFO method for optimizing, learning, and conducting randomized searches is the genetic algorithms. GA simulates mutagenesis and other steps of the evolution of life



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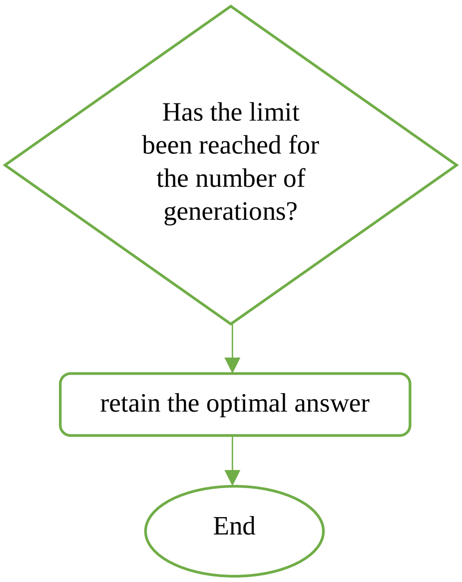

Figure 3. The Proposed GA Flowchart

Crossing and choosing, on the premise that great people tend to generate even better people. The first step of GA is to generate a collection of initial, randomly selected solution to the issue. As a precondition, the result set must be generated randomly before its worth can be evaluated. One way to achieve this is to create an index of fitness that ranks all of the solutions according to how well they fit the problem in this as shown in figure 3.

After calculating a fitness value, the most suitable list is revised by removing the items that did not meet the criteria. Then, the optimal function of fitness is selected to serve as the foundation for the one that follows utilizing the Roulette-Wheel method. The fit individual gets to pass on their exceptional health and wellbeing to the generations that come after them. In evolutionary processes, the process of selection is used to choose organisms. The most beneficial values are selected by eliminating the worse ones in terms of fitness. By choosing the strongest and healthiest members of the community, it establishes a breeding pool. Each string is reproduced and added to the coupling pool in a stochastic method. See Figure 3 for an operational diagram of how to get the EKF noisy covariance matrix values using GA.

The replication process is executed using a configuration similar to a roulette wheel. The selected set of answers will use crossovers between genetic algorithms in subsequent generations. With a random selection of two string within the mated pool, a crossing operation may be performed with a particular likelihood to generate two new strings by subjecting both of them to crossover at a randomly selected place. Mutations change the value of any of the characters in a string at randomness by moving them from 0 to 1 or 1 to 0. Mutation's frequency is used to choose the progeny. The method uses a convergence of decades to choose the best people for expressing the ideal solution. Estimation of SOC using the SFO-based EKF technique is presented in this study. By fine-tuning the EKF estimator, SFO boosts EV's responsiveness. A key component of EKF effectiveness for precise state determination is the variability of the covariance matrix (Q & R), which are optimally, determined using the SFO technique. SFO is an algorithm based on the population that is metaheuristic and influenced by the way nature behaves. It is very storage space and performance effective and uses just elementary mathematical operations. Instead of being trapped at the local ideal point, the SFO finds the optimum global approach as professionals, much like a sunflower moving regarding the sun. One major benefit of SFO is that it does not use derivatives while assessing fitness functions.

$$P_{g,j} = \frac{Q_r}{4\pi s_{e,j}^2} \qquad (3)$$

where e, j is the distances from the sun (Q_r) to the jth blossom and is the heat $(P_{g,j})$ that it has acquired.

$$\overrightarrow{R_k} = \frac{Y^* - Y_j}{||Y^* - Y_j||},\ j = 1,2 \dots \dots m \qquad (4)$$

Where Y_j signifies the optimal solution and stands for the existing one. Using Equation 5, we can determine the sunflower's azimuth with respect to the sun.

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$$e_j = Q_j(\left|\left|Y_j - Y_{j+1}\right|\right|) \times \left|\left|Y_j - Y_{j+1}\right|\right| \qquad (5)$$

The chance of pollination process, where e_j is the constant number that characterises plants' "inertial" expulsion, $Q_j\left(\left|\left|Y_j - Y_{j+1}\right|\right|\right)$ is used to establish a new individual at randomised point, in this case, by pollinating its next neighbours.

$$e_m = \frac{Y_m - Y_n}{2 \times m} \qquad (6)$$

where $Y_m - Y_n$ is the overall number of blossoms in the overall population and is the disparity among the lower and upper limit numbers. In (7), the new planting is taken into account.

$$\overrightarrow{Y_{k+1}} = \overrightarrow{Y_j} + e_j \times \overrightarrow{R_j} \qquad (7)$$

PSO is an AI-inspired probabilistic population-cantered method. In regards to storage and processing performance, it is extremely effective and it just needs elementary mathematics operations. Using an approach similar to that of flocking of animals, the PSO discovers the best resolution for exploring area. The initialisation of the swarming populations (m) according to the problem's lower and higher limits is the first step in employing PSO. The swarming population's velocities (u), accelerating coefficient ($d_1 * s_1$), inertial weights (z), and maximal repetitions (next) should all be initialised. The function of objectives (e) is used to calculate the fitness rating for all populations when each swarm populations is initialised. When solving a minimisation or optimisation issue, the physical fitness value and swarming membership are arranged in either descending or ascending control, respectively. Compute the updated velocities using the global average highest point (h_c) and your individual best positioning (q_c), the next stage in PSO. The revised velocity is used to update the swarming population's heading. Equations 8 and 9 modify the swarm's momentum and individuals.

$$u_j^+ = zu_j + d_1 * s_1 * \left(q_c - y_j\right) + d_2 * s_2 * (h_c - y_j) \qquad (8)$$

$$Y_j^+ = y_j + u_j^+ \qquad (9)$$

where, $s_1\ and\ s_2$ are real numbers between zero and one that are generated uniformly. Assuming that the parameter f is to be minimised, Equation 5.10 updates the individual optimal spot and

$$h_c \in arg_{qc}n\ e(q_c^+) \qquad (10)$$

$$Y_{l+1} = By_l + Cv_l + z_l \qquad (11)$$

$$X_l = Dy_l + Ev_l + u_l \qquad (12)$$

Where: State parameters (SOC, RC voltage) are represented by y_l. v_l: Present (input). Results (voltage) = X_l. z_l, u_l: Measurements and treatment of noise. Systems matrix B, C, D, E.

$$P = e(p_1, p_2, \ldots., p_m) \qquad (13)$$

$$S = e(s_1, s_2, \ldots., s_m) \qquad (14)$$

Here, p_j are the set of variables for the method of noisy variances that SFO optimises. Here, s_j are the settings for measuring noisy variances that SFO optimises.

$$Q_{l|l-1} = BQ_{l-1|l-1}B^V + P \qquad (15)$$

$$y_{l|l-1} = BY_{l-1|l-1} + Cv_l \qquad (16)$$

The confusion of the projected states is described by the expected errors correlation matrices, $Q_{l|l-1}$: The erroneous covariant matrix that had been altered in the preceding phase. A ⊦: The matrix of state transitions transposed. The projected state vectors, $y_{l|l-1}$, is approximately calculated at time k k using the previously calculated state as a starting point. $Y_{l-1|l-1}$: the stage of the vectors that has been updated from the preceding time step.

$$L_l = Q_{l|l-1}D^V(DQ_{l|l-1}D^V + S)^{-1} \qquad (17)$$

$$y_{l|l} = y_{l|l-1} + L_l(x_l - Dy_{l|l-1}) \qquad (18)$$

l : Kalman Gain, which calculates the amount by which the evaluation ought to be used to adjust the anticipated state. D^V: The result of the matrix's transposition. (⋅) −1: Matrix inversion. $y_{l|l}$: condition vector that has been rectified, including measurements taken at time l. x_l: $DQ_{l|l-1}$. The predicted outcome according to the state-space approach, according to measurements at time l. the discrepancy among reality and projected outcomes, denoted as $x_l - Dy_{l|l-1}$, is an indication of variation or residue. One recent proposal for a metaheuristic technique that

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uses intelligent swarms is Harris Hawks's optimisation. The HHO's superior efficacy in addressing a wide variety of complicated issues, together with its relative ease of use, durability, and effectiveness, have earned it a reputation as a potent optimisation tool.

6. Results Analysis and Discussion

An established method for estimating nonlinear states is the Extended Kalman Filter. When it comes to prediction estimating, however, EKF performs worse when the noisy coefficient matrices Q and R are not chosen well. The optimisation procedure is used to get the optimum quantities for the noisy coefficient matrices after the effect evaluation was completed done using the trial-and-error technique. The EKF technique is then used to estimate SOC based on the values of the Q and R matrices. To mitigate the impact of operational and measurements noise, an optimised EKF is used. It also continually updates the batteries modelling settings revised using the recurrent lowest-squares approach for variables with forgetfulness factors. We put the suggested estimate to the test by simulating a battery discharge scenario with a steady current. When contrasted with other optimisation algorithms, the trial-and-error approach, the genetic approach, PSO, and HHO all display lower efficiency indices for SFO. These indices include maximal error, mean quadratic error, root mean square error of SOC estimate, and MAE. In addition to being precise, the suggested approach merges fast, regardless of how off the starting SOC appears.

6.1. Maximum Error (Max. Error): This is the maximum absolute difference between the simulated or tested SOC and the real SOC.

6.2. Mean Absolute Error (MAE): The MAE is the sum of all time steps' actual discrepancies among observed and predicted SOC.

6.3. Mean squared error (MSE): The MSE measures how far off the actual and predicted SOC values are from one another.

6.4. Root-mean-squared error (RMSE): The RMSE measures the dispersion of estimate mistakes and is equal to three times the MSE.

Table 1: Evaluation of five methods for SOC estimate and comparison of their outcomes

Models	Max. Error
TR-EKF	0.0097
GA-EKF	0.0020
PSO-EKF	0.0024
HHO-EKF	0.00010
SFO-EKF	7.18e-04

When looking at the greatest SOC estimate errors of several designs, the SFO-EKF approach stands up as the best. With an error of 0.0097, the trial-and-error EKF (TR-EKF) is the least accurate method because it uses non-optimized noisy correlation matrix. By optimising their parameters, the GA-EKF and the PSO-EKF achieve considerable reductions in error—0.0020 and 0.0024, respectively—demonstrating modest improvements. The efficacy of the HHO-EKF in reducing SOC estimate mistakes is shown by its much smaller error of 0.00010. Although it is somewhat higher than HHO-EKF, the SFO-EKF modelling still significantly surpasses GA-EKF, PSO-EKF, and TR-EKF, with an error of 7.18×10^{-4} (or 0.000718). From figure 4 authors can conclude that the SFO-EKF is a strong contender, especially for applications in real time, because to its balanced accuracy, computing effectiveness, and resilience.

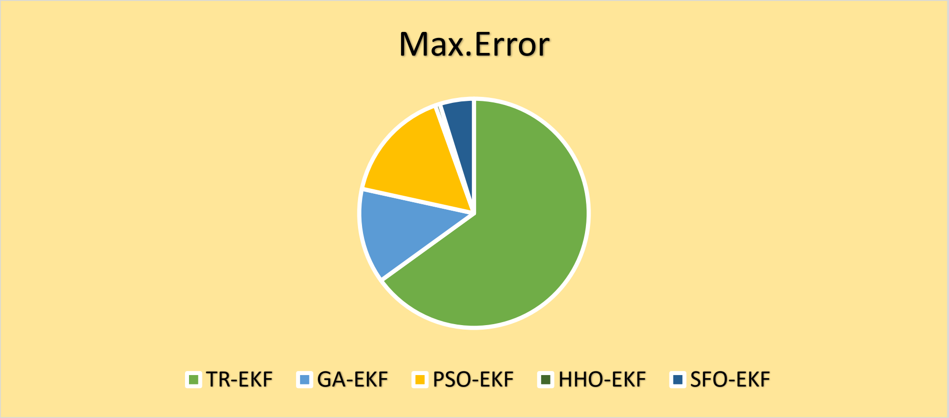

Figure 4. Evaluation of ML models in comparison to more traditional approaches.

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Table 2: Results of MAE Statistical Measures

Models	MAE
TR-EKF	5.94e-04
GA-EKF	5.07e-04
PSO-EKF	9.02e-04
HHO-EKF	4.60e-04
SFO-EKF	2.01e-04

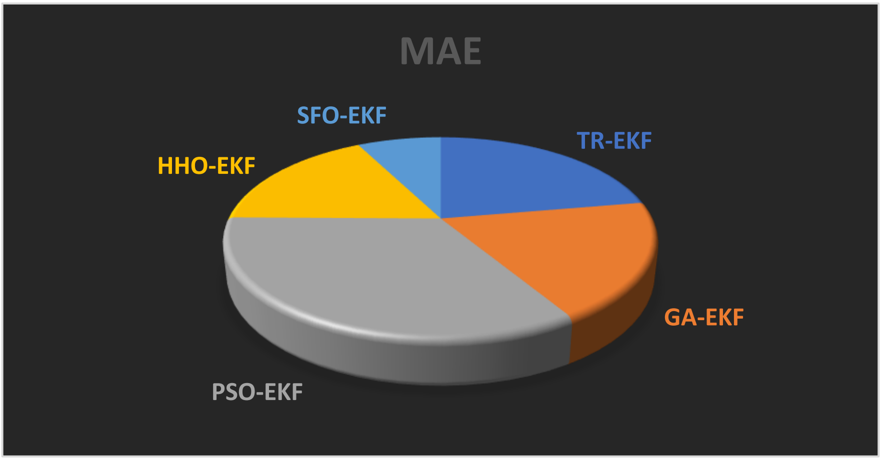

Figure 5. Comparing ML models to more conventional methods for evaluation.

When comparing the MAE of the various SOC estimate methods as shown in figure 5, the SFO-EKF technique stands out as the most accurate. The absence of optimised noise matrices for covariance causes the TR-EKF to attain a mediocre accuracy, as shown by its MAE of 5.94e-04. The GA-EKF approach shows greater growth than the PSO-EKF framework, exhibiting a MAE of 5.07e-04 and 9.02e-04, accordingly; the PSO-EKF model has a somewhat larger inaccuracy. By further reducing the MAE to 4.60e-04, the HHO-EKF proves its efficacy in attaining more precise SOC estimates. When compared to the other approaches, SFO-EKF achieves the best performance, with a minimum MAE of 2.01e-04. The SFO-EKF is a great option for SOC estimate in BMSs since it reduces average errors and improves precision in general.

Table 3: Statistical Measures for MSE Outcomes

Models	MSE
TR-EKF	2.32e-06
GA-EKF	3.27e-07
PSO-EKF	3.39e-07
HHO-EKF	2.92e-07
SFO-EKF	4.15e-08

The SFO-EKF approach stands out from the other SOC estimate approaches when comparing their MSEs. At 2.32e-06, the TR-EKF has the highest MSE, suggesting that there are substantial estimate errors caused by non-optimized variables. Outcomes are improved using optimisation approaches such as GA-EKF and PSO-EKF, which provide minor decreases in estimate error with MSE values of 3.27e-07 and 3.39e-07, respectively. The HHO-EKF improves precision even more, reaching a MSE of 2.92e-07. In contrast, the SFO-EKF minimises the proportional discrepancies among reality and anticipated SOC values largely, as seen by its most modest MSE of 4.15e-08 as shown in figure 6. This finding establishes that the SFO method outperforms the other approaches tested when it comes to optimising EKF variables for dependable and very precise SOC estimate.

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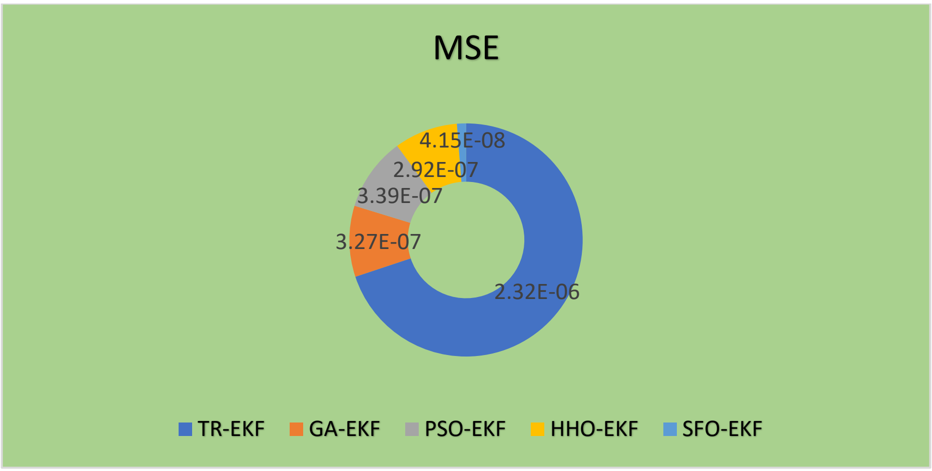

Figure 6. Efficacy of different systems

Table 4: Exploratory DL models in relation to proposed methods

Models	RMSE
TR-EKF	0.0011
GA-EKF	4.77e-04
PSO-EKF	4.89e-04
HHO-EKF	4.38e-04
SFO-EKF	1.77e-04

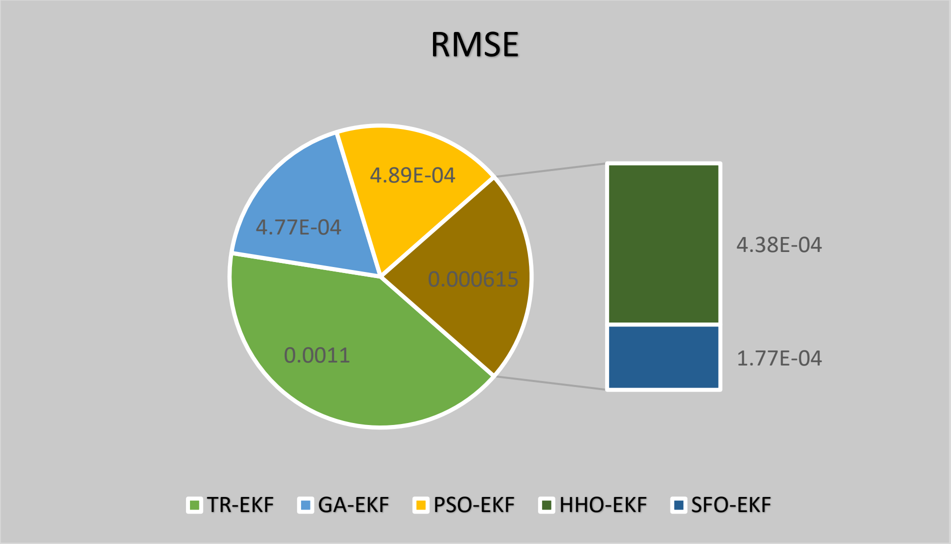

Figure 7. Effectiveness of different models

The SFO-EKF methodology stands out for its exceptional accuracy when compared to the other SOC estimating techniques in terms of RMSE. With an RMSE of 0.0011, the TR-EKF is the least reliable of the bunch since its settings aren't optimised as shown in figure 7. While PSO-EKF is slightly slower than GA-EKF, both exhibit substantial growth with RMSE values of 4.89e-04 and 4.77e-04, correspondingly. By using more efficient optimisation, HHO-EKF is able to further decrease the RMSE to 4.38e-04, demonstrating improved efficiency. But, when compared to all other approaches, the SFO-EKF delivers the best results with an RMSE of just 1.77e-04. This proves that the SFO-EKF is a highly trustworthy option among existing battery's management software, as it consistently and accurately estimates SOC with little error.

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7. Conclusion and Future Work

For battery packs for electric vehicles, the suggested SFO-EKF model is a huge step forward in estimating the SOC. In order to overcome the drawbacks of traditional Extended Kalman Filter (EKF) techniques—like the need to manually adjust the background noise covariance matrix ratios (Q and R)—this study presents the SFO method. To estimate SOC with accuracy, robustness, and computing efficiency, SFO effectively traverses search space, avoiding optimal local conditions. According to the simulations findings, the SFO-EKF approach is superior compared to other optimization-based designs, such as models that use Genetic Algorithm (GA), Particle Swarm Optimisation (PSO), and Harris Hawks Optimisation (HHO), as well as classical EKF methods. SFO-EKF proves its exceptional efficiency by consistently delivering the lowest MSE and Root Mean Square Error (RMSE) across a range of dynamic as well as static circumstances. It is also well suited for use in immediate form systems for managing batteries since the model converges quickly and preserves a high level of correctness even while operating with baseline SOC errors. This study displays the SFO-EKF model's capacity to increase electric car battery capacity and lifespan by making SOC estimates more reliable and efficient. If researchers are interested in finding ways to make SFO-EKF even more scalable in the face of changing and unpredictable operating situations, they may look into merging it with adaptive approaches.

– Future work

To further improve the capacity and efficacy under different operational situations, future study should investigate integrating SFO-EKF with adaptable or hybrids optimisation approaches. Its potential use in electric vehicles and battery backup systems may be further expanded if it were to be applied to other kinds of battery and real-world vehicle situations.

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