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Adaptive filter algorithms for state of charge estimation methods: A comprehensive review

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ABSTRACT

Battery management system is compulsory for long life and effective utilization of lithium ion battery. State of charge (SOC) is key parameter of battery management system. SOC estimation isn't an easy job. Effective estimation of SOC involves complex algorithms where. Conventional methods of SOC estimation does not take continuously varying battery parameters into account thus large noise in both voltage and current signal are observed resulting in inaccurate estimation of SOC. Therefore, in order to improve the accuracy and precision in SOC estimation, improved adaptive algorithms with better filtering are employed and discussed in this paper. These adaptive algorithms calculate time varying battery parameters and SOC estimation are performed while bringing both time scales into account. These time scales may be slow-varying characteristics or fast-varying characteristics of battery. Some experimentations papers have proved that these adaptive filter algorithms protect battery from severe degradation and accurately calculate battery SOC. This paper reviews all previously known adaptive filter algorithms, which is the future of the electrical vehicles. At the end, a comparison is built based upon recent papers which talked on SOC at their differences in control strategies, efficiency, effectiveness, reliability, computational time and cost.

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1. INTRODUCTION

Electrical energy is much necessary to support life in current era whereas advancement in electrification has raised our dependency on electric and electronic devices [1]. Human efforts have been minimized by the use of smart devices. Electrical machines perform desired jobs with higher accuracy and efficiency [2], [3]. These power devices offer smart control for operations. The advancement in electrical technology has made it possible to operate electrical power devices even in absence of nearby power outlets [4]. The electric vehicle mobility is only made possible by the use of efficient storage devices [5]. These high energy storage capacity batteries have capability to support diverse power applications. A mobile phone to an electric vehicle, every electrically driven machine depends on batteries for their operation as a consequence of advancement in battery technology [6] Electric vehicle is getting high fame and appreciation by the manufacturers and customers [7]. Electric car requires a consistent flow of energy to perform efficient zero emission transportation. The power sources like wind and solar cannot be employed for charging electric vehicles [8], [9]. This high supply demand chain of energy is only ensured by use of batteries for complete regulated balanced power supply for operations [10].

This increasing use of power devices has induced a high load on energy storage devices to support machine functionality for longer time This long-time battery power backup is provided by the development of lithium-ion batteries [11]. This battery has revolutionized battery technology by offering a very high specific energy and high energy density [12]. This battery pack is consisted of series of lithium-based cells. lithium-ion battery is considered as powerhouse for electrically driven machines. lithium is lightest metal with low standard reduction potential thus offering high energy density [13], [14]. Meanwhile, lithium is highly reactive as well so a proper battery management system is really necessary to ensure safety and long life of lithium-based batteries [15]. Battery management system (BMS) is important for better utilization and implementation of battery's potential and capacity to maximize the cycle life of Battery [16]. One of the very important features of BMS is estimation of state of charge [17]. An illustration of BMS is shown in Figure 1. One of the important parameters for battery safety is state of charge (SOC). SOC maintains battery in safe limits of charge and discharge. SOC is actually present amount of battery capacity andenables batteries to maintain certain levels of charge and discharge that could enhance its life span [18]. SOC acts as major parameter for management of batteries. Accurate estimation of SOC provides system stability and reduces harmful effects of battery aging on entire system of operation [19] and itavoids unsuitable overcharge and over discharge [20].

SOC is not calculated directly. It involves battery characteristics and parameters. The conventional SOC estimation methods like coulomb counting, model based, pen circuit voltage and internal resistance methods suffers through accumulation of few errors leading to major glitch in output resulting in inaccurate estimation of SOC [21]. Additionally, many chemical changes in battery and battery parameters are not taken into consideration fully so there is always a chance of error in estimation of exact SOC. Due to manufacturing differences, all batteries do not show a linear behavior towards charging and discharging [22]. This conditzion results in voltage imbalance for different batteries. Therefore, a cell showing with 100% SOC may not necessarily indicate the actual SOC of the battery. accurate estimation of SOC could only be performed by continuous monitoring of each cell in battery [23]. This is made possible through adaptive higher level of precise adaptive accurate algorithms [24]. In this paper adaptive filter algorithms for SOC estimation are discussed in detail. A comparative analysis is drawn based upon certain parameters.

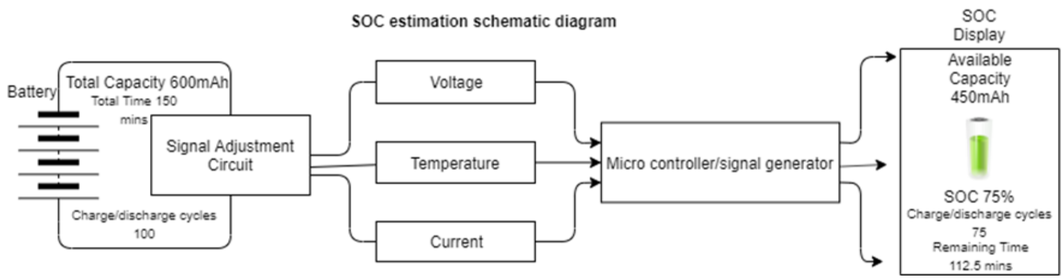

Figure 1. SOC estimation schematic diagram

2. ADAPTIVE FILTER ALGORITHM

The adaptive filter algorithems are widely used for accurate estimation of battery SOC. Adaptive filter algorithms provides a lossless transformation and low system complexity. Adaptive filter algorithms are of seven basic types. Figure 2 illustrates the types of adaptive filter algorithms for SOC estimation.

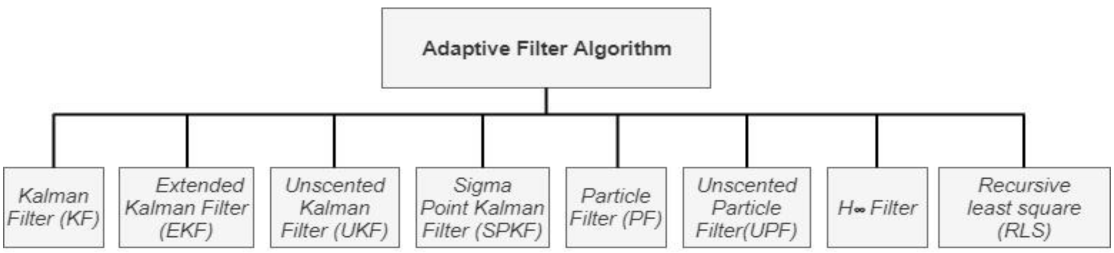

Figure 2. Types of adaptive filter algorithms for soc estimation

2.1. Kalman filter (KF)

Kalman filter is one of the well-known techniques to estimate of SOC for the battery system. This method is also used for target tracking and navigation. This method provides wonderful solution for state observation and prediction. Kalman filter effectively estimates SOC of battery by filtering external disturbances and noises caused due to Gaussian distribution. This method involves high mathematical calculations and particular sampling interval. SOC of battery calculated by this method is thought to be more accurate. One of the more advantageous fact about Kalman filter is that it can assess system conditions like temperature and model parameters like noise with a better accuracy. Kalman filter estimates SOC as well as state parameters of battery. The key feature of Kalman filter is that it can minimize sum of squared errors between actual value and estimated value of states. This filter operates in two states. The first stage is predictive stage. In the first stage, state parameters and SOC are estimated along with gaussian noise. The second stage is called corrector stage. At this stage, noise and external disturbances are filtered and accurate estimation of battery SOC and parameters are obtained. Kalman filter predicts current state $X_k$of system from earlier estimated state $X_{k_{-1}}$ and then predicts SOC after filtering results [25].

$$X_{k_{+1}}= A_{kX_k} + B_{kU_k} + W_K \tag{14}$$

$$Y_{+1}= C_{kX_k} + D_{kU_k} + V_K \tag{15}$$

Here *X* is state of the system, *U* is the control input to the system, *W* is processing noise governed by gaussian distribution, *Y* is measured input, *V* is measured external noise while A, B, C, D are the covariance matrixes. As, the system is dynamic so these matrixes are time varying. The overall system dynamics are expressed through these matrixes given in [26]. In Kalman filtering, nonideal factors are reduced to zero and precise estimation of battery SOC is carried out. Kalman filter has a diverse utility. It can be applied for effective SOC estimation of almost all types of batteries because its estimation is based upon battery's chemical properties not only its terminal voltage. Kalman filter also helps to measure battery state of health where it calculates internal resistance or self-impedance of each cell inside battery. Experimentally, Kalman filter implementation proved that ohmic resistances inside battery are not uniform which may sometimes lead to overcharge/discharge which has been discussed in [27]. As battery itself is a highly nonlinear system. Along other state transitions, it also undergoes through self-discharge and corrosion. A stochastic fuzzy neural network based extended Kalman filter particularly utilized where the acceptable estimate for SOC is to be calculated. Whereas maximum error of SOC estimation is 0.6% when compared to real SOC upon discharge test [28].

2.2. Extended Kalman filter (EKF)

Battery is a highly non-linear time varying system. It is quite hard to calculate exact SOC of battery due to its nonlinearity and various electrochemical processes. Extended Kalman filter is sophisticated mechanism where it is based upon extended Kalman filter greatly depends upon battery model and its electrochemical characteristics. System accuracy depends upon electrodynamics of battery and system noise, mean value of voltage, pertinence, covariance matrix [29]. Extended Kalman filter is used to measure battery SOC with improved accuracy and adopts system conditions. Extended Kalman filter minimizes mean of squared errors during the process and filter the estimations using measured noise covariance. Identification and estimation of the model parameters is greatly improved by this genetic algorithm [30]. Extended Kalman filter provides approximation of nonlinearity. Some experimental results showed that extended Kalman filter has better accuracy. The estimated value has smaller initial error of $\pm 5\%$ to real values [31]. Extended Kalman filter is employed to reduce the process noise thus model achieves most precise battery SOC results from unknown initial SOC. In particular lithium iron phosphete $LiFePO4$ battery, dual extended Kalman filter estimates battery SOC with maximum error of 4% [32]. There is another modification of Kalman filter called adoptive extended Kalman filter which uses improved Thevenin battery model for correct estimation of robust SOC of li-ion battery. The simulation results of adopted extended Kalman filter are more accurate and its system stability is more reliable then extended Kalman filter. It is confirmed through experimentation as well as from theory that adoptive extended Kalman filter estimated battery SOC by decreasing error from 3.16% to 1.06%.

2.3. Unscented Kalman filter (UKF)

Extended Kalman filter provides solution of SOC estimation for nonlinearities of first and second order battery model. It is not necessary that for each type of battery to have same order. There may exist some big errors especially when state-space model is nonlinear and abnormal in behavior. In previous models discuissed above, estimated voltage was compared to the measured voltage. This difference between these two voltages was considered as correction term which adjusts battery SOC. This method is not effective for models involving significant errors. In order to resolve this problem, a modified method for battery SOC estimation was introduced for all state-space models with higher order of nonlinearity. This method is called unscented Kalman filter. This method helps to estimate all random parameters propagating in any nonlinear system. Here state distribution is represented as sigma points. These sigma points are actually mean and covariance of the state distribution in a complete nonlinear system. Unscented Kalman filter offers more accuracy and robustness as compare to extended Kalman filter. The unscented Kalman filter brings all random parameters under consideration in real time. This method uses OCV battery model with resistance connected in series. The implementation of Kalman filter reduces real mean square (RMS) errors of all cases to 3.1%, from 6% [33]. Battery voltage model and coulomb counting method is combined through unscented Kalman filter to determine battery parameters and state of charge. Coulomb counting method based dynamic SOC estimation model is developed with a correction factor for reducing error and increasing output precision. In particular LiFePO4 battery, this method reduces RMS errors to less than 3%. This is the best strategy to estimate SOC of each unit within battery. Unscented Kalman filter accepts unit to unit variation, observe, evaluate and optimize SOC value for each unit within battery. Unscented Kalman filter is a real time SOC estimation and error correction system so it has a wonderful ability to adjust with changing environment and time varying parameters of state. Unscented Kalman filter protects battery from over charging/discharging thus enhancing life of the battery [34]. Unscented Kalman filter is advantage of being closed loop which governs self-corrections. An adaptive unscented Kalman filter is designed for online estimation of SOC of electric vehicle batteries. This method has an adaptivity to attain conditions and predict noise covariances through output voltage sequence of zero-state hysteresis battery model. This adoptive algorithm has very low computational load so recursive SOC estimation of battery can be performed.

2.4. Sigma point Kalman filter (SPKF)

In previous battery SOC estimation methods, battery model adopted was highly complex and involved greater nonlinearity. This behavior of the system is not easy to understand. This type of system involves multiple parameters. The SOC estimation of battery completely depends on state parameters. In order to calculate state parameters and SOC of battery an improved algorithm from unscented Kalman filter is introduced. This new improved algorithm is called sigma point Kalman filter. Sigma point Kalman filters uses sets of sigma points which represents mean and covariance of system. Mean and covariance of the model helps to calculate state parameters. This provides sufficient electrodynamic information for further estimation of SOC of battery. Sigma point Kalman filter is used widely for battery SOC estimation because it involves least complexity and takes less computation time. This model does not need Jacobian matrices to compute original values or derivatives. Sigma points provide simpler and sufficient replacement to this complex electrochemical data set of battery. Experimental results proved that SOC estimation of LiFeP04 battery through sigma points Kalman filter offers more accuracy and high robustness [35]. The convergence behavior of sigma point Kalman filter makes it robust solution for SOC estimation of lithiumion batteries. Sigma point Kalman filter is cost efficient to implement. It involves a very low memory space.

2.5. Particle filter (PF)

Most lithium-ion batteries in electric vehicles possess micro hysteresis during partial cycling. This micro hysteresis leads to major variations in state parameters of battery. It becomes hard for common Kalman filter to assess these parameters accurately [36]. Particle filter algorithm is applied to estimate states. Particle filter algorithm estimates probability density function using Monte Carlo simulation technique with set of random particles. Particle filter is effective even in non-gaussian distributions. Particle filters stochastically model behavior multimodal distributed lithium-ion battery with hysteresis in open circuit voltage. Particle filter estimates state of health of battery and state of charge of battery. Total available charge and battery capacity is represented by set of particles of any sample size. These sets do not have same size and each represent a particular quantity. Particle filter uses these sets of information to approximate state of charge and state of health of battery as well [37]. This algorithm is different in nature that it calculates an error free correct value before computation by stochastic processes while all previous algorithms correct value at the end by filtering error from final results. This particular filter enhances efficiency, robustness and addresses the hysteresis within battery. Unscented particle filter algorithm was devised the approximation purposes for almost all high-power lithium-ion batteries. Model considered was studied under the influence of drift noise, temperature, charging and discharging rate and operational. This type of filter method reduces root mean squared error and maximum absolute error to 12.6% while this error in extended Kalman filter and unscented Kalman filter was 30.2% [20].

2.6. Unscented particle filter

SOC estimation method is quite influenced by the battery characteristics stated in [38], [39]. By using common Kalman filter and particle filter there are a big probability of error generation [40]. So, for the accurate SOC estimation of battery in EVs, modified algorithm-based methodology called unscented particle filter is introduced in [41]. The advantage of using unscented particle filter is its ability to sharply determine search range which helps in identification of battery model parameters. So, the probability of system failure is reduced and effective SOC estimation control is established, having high recognition accuracy [42]. Unscented particle filter can realize online dynamic parameters to enhance accuracy. In addition, unscented particle filter considers the complex environmental and operational conditions for battery in electric vehicles. Unscented particle filter has higher accuracy and system stability as compared to SOC estimation method based on least square unscented particle filter [43], [44]. This strategy uses for reduction of the computational complexity of system. This method helps genetic algorithm to converge quickly and accurately. The proposed algorithm is suitable for complex system identifications [45]. Finally, this algorithm will improve the accuracy of SOC estimation. This algorithm considers the accuracy, complexity, dynamic characteristics, temperature as well as some of the other factors power battery models. Some of these battery models are Rind model, Thevenin model, partnership for a new generation of vehicles (PNGV) model, and general nonlinear (GNL) model, and few more given in [46], [47].

2.7. H∞ filter

H∞ is second order RC filter circuit. This filter is effective for high accuracy and robustness in uncertain environments. It is designed to estimate battery SOC considering time varying parameters. This is advantageous technique to estimate SOC because it considers effects of real time shift in characteristics of state parameters. Process noise and measurement noise characteristics are not needed to be pre-defined as it monitors real time shift in their values. This type of filter achieves SOC estimation with an acceptable error of 2.49% [48]. Adoptive H∞ filter uses universal linear model and some free parameters to estimate battery SOC. These free parameters are identified and recorded as functions of battery SOC. These functions are calculated through polynomial expression and least square methods. Time varying parameters are tuned and approximated to reduce system complexity minimize computation time and memory utility. This adoptive H∞ filter provides noise attenuation and enhances output precision [49]. This type of filter possesses high accuracy, low computational time and involves low cost of implementation.

2.8. Recursive least square (RLS)

Recursive least square is another method been implemented in time varying systems for SOC. It represents dynamic voltage behavior and calibrates battery parameters. This is adoptive dynamic model with a forgetting factor with recursive least squares algorithm. Recursive least square uses recurrent neural network for adaptive model-based estimation of battery SOC. This type of SOC estimation uses battery model with three major parts. The first is Nernst equation. This Nernst equation is used to express relationship between SOC and OCV. Second part is a zero-state hysteresis correction term for parameter correction of hysteresis effect and third part is first-order RC network for stimulation of transient response and relaxation effect. This method predicts voltage of battery with negligible error of 0.1% as given in [50]. Recurrent neural network based SOC predictor uses full operating range of battery pack independent of over/under charged cells. This SOC predictor is based upon recursive least square algorithm with time varying forgetting factor. This advanced method helps to understand dynamic behavior of the Li-ion battery cell and its dynamic parameters. SOC-estimation error and measurement noise are calculated and gross output value is reduced to genuine value which results in higher precision of SOC estimated values in real time. Artificial neural network makes it possible to check dependencies and an uncertainty involved in SOC estimation and helps to understand nonlinear dynamic and complex behavior of battery system. A very large number of data points, representing all battery levels and state parameters helps to produce most accurate estimation of battery SOC [51]. Battery SOC can be calculated through this method with high accuracy and acceptable error of 2.121%.

3. COMPARATIVE ANALYSIS OF ADAPTIVE FILTER ALGORITHM FOR SOC ESTIMATION OF LITHIUM ION BATTERIES

Table 1. Shows the comparative analysis of SOC estimation methods for lithium ion battery with average error and cost. Moreover, the advantages and disadvantages of each is given. An effective comparison is drawn between all the algorithms based upon their average accuracy.

Table 1. Comparative analysis of SOC estimation methods for lithium ion battery

S.#	Name	Avg. errors	Cost	System complexity	Advantage	Disadvantage	Avg. accuracy	Computation time
1	KF [28], [34]	$\leq \pm 1.76\%$	High	High	High accuracy	Complex computation	≥98.5%	Low
2	EKF [39], [52]	$\leq \pm 1\%$	High	High	Dynamic state prediction	Limited robustness	≥99%	Low
3	UKF [33], [34], [41]	$\leq \pm 4\%$	Medium	Medium	Nonlinear compatibility	Poor robustness	≥97%	Low
4	SPKF [38], [53]	$\leq \pm 2\%$	Low	Low	Better robustness	Heavy calculation	≥98%	Medium
5	PF [37], [42]	$\leq \pm 1.02\%$	High	High	Fast computation	Complex calculations	≥99%	Low
6	H∞ Filter [54]	$\leq \pm 2.49\%$	Low	Medium	High time efficiency	Hysteresis effects accuracy	≥97.5%	Low
7	RLS [50], [55], [56]	$\leq \pm 1.03\%$	High	High	Eliminates noise	System instability	≥99%	Low
8	UPF [20], [41]	$\leq \pm 2.6\%$	High	High	Online error reduction	Large memory unit	≥98.2%	Low

4. CONCLUSION

This paper reviews multiple algorithms for SOC estimation of lithium ion battery. A detailed study of each adaptive filter algorithm is done in this paper. Each adaptive filter algorithm is discussed in terms of its control concept, efficiency, reliability, average error and maximum accuracy. This paper reviewed adaptive filter algorithms for SOC estimation of lithium ion batteries. Each method is explained based on its operational strategy and its impacts on estimation precision. Each method is being analyzed on different operational conditions. This paper provides a comparative analysis of all known adaptive filter algorithms for SOC estimation of lithium ion battery. In electric cars using lithium ion batteries SOC estimator acts as fuel gauge. Accurate estimation of battery SOC isn't easy. This paper presents some basic knowledge regarding SOC estimation concepts using adaptive filter algorithms and their significance.

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