Piecewise Model-Based Online Prognosis of Lithium-Ion Batteries Using Particle Filters

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ABSTRACT Lithium-ion batteries are used as energy sources for energy storage systems, electric vehicles, consumer electronic devices and much more. Prediction of the remaining useful life (RUL) of such sources is vital to improve the safety and reliability of battery-powered systems. Even though several prognostic methods have been extensively explored for the RUL prediction of lithium-ion batteries, these methods are focused on adopting a single empirical / phenomenological degradation model which best describes the degradation behavior. However, certain lithium-ion battery materials exhibit two distinct degradation behaviors with an evident *inflection point*. In such cases, a single empirical model no longer holds good. Hence, we propose a *piecewise degradation model* along with a novel methodology to determine the inflection point. The proposed model is incorporated into a particle filter framework to predict the battery's degradation trajectories. The effectiveness of the proposed model is verified by adding a 50dB noise to the measurement data. The prognostic results of the proposed piecewise model are compared with the existing single empirical model. We use prediction error and execution time as the prognostic metrics for comparison.

INDEX TERMS Particle filters, remaining useful life, lithium-ion batteries, piecewise degradation model, inflection point.

I. INTRODUCTION

Due to their high energy density and light weight, lithium-ion batteries are widely employed in portable electronics, mobile devices, and electric vehicles as the main source of energy. However, the lifespan and performance of the battery tends to deteriorate during its operation with cycling and aging. Hence, diagnosis and prognosis of capacity degradation are essential for the safe and reliable usage of these battery powered devices. Specifically, predicting the remaining useful life of lithium-ion batteries is a widely researched domain as it reduces the risk of undue downtime or unforeseen catastrophic failures by giving advance warnings and providing the user ample time to take necessary corrective measures.

Battery degradation cannot be measured directly, and battery capacity is the most widely used health indicator to deduce the state of health (SoH) of the battery. Battery capacity is defined as the amount of electric charge the battery can hold in its fully charged state. Hence, battery capacity decreases as the battery degrades. In general, end of performance (EoP) of battery is set as the time instant at which the maximum available battery capacity is reduced to 80% of its rated capacity.

In general, most RUL prediction methods can be categorized as data-driven methods, model-based and hybrid methods. Data-driven methods extract useful features from the degradation data using statistical and machine learning approaches. These data-driven methods learn the inherent degradation trend of the system from the extracted features and use it for RUL estimation. Data-driven methods do not require any prior knowledge about the system's behavior. Prognosis within the domain of data-driven approaches can be broadly categorized into statistical methods and machine learning approaches. In the sub-domain of statistical methods, Barraza *et al.* [1] proposed three autoregressive models with exogenous variables (ARX) with self-starting capabilities for RUL estimation of aluminum plate based on crack growth. The proposed models do not require large historical

data unlike most of the statistical approaches available in literature. These ARX models rely only on available knowledge of the degradation process and operating conditions to estimate the RUL. Also, the authors incorporated recursive parameter estimation techniques along with a forgetting factor for the ARX model to adapt to changing operating conditions. Similarly, Pham *et al.* [2] proposed a hybrid model combining linear autoregressive moving average (ARMA) model and the non-linear generalized autoregressive conditional heteroscedasticity (GARCH) model to predict the fault condition of methane compressors in a petrochemical plant. However, these statistical approaches work well only when there is at least one set of run-to-failure data available and also for modeling lesser complex failures in the system.

Machine learning based approaches, on the other hand, include neural networks [3], fuzzy logic [4], support vector machine [5], relevance vector machine [6] and many others. Loutas *et al.* [7] proposed a probabilistic support vector regression (e-SVR) method for prediction of RUL of ball bearings. The authors had performed time-frequency analysis on the available historical data and proposed a new feature named Wiener entropy (WE) for the purpose of condition monitoring. The RUL prediction of the e-SVR model using WE under two different operating conditions was analyzed. Liu *et al.* [8] proposed a deep learning based long short-term memory (LSTM) network along with a Bayesian model averaging strategy for RUL prediction of lithium-ion batteries. Moreover, several neuro-fuzzy inference systems have also been developed for prediction of machine condition in mechanical systems using the vibration data collected from the equipment [9], [10].

However, the major drawback of all the above-mentioned prognostic approaches is the dependency on large amount of historical failure data for training the data-driven model. Moreover, data pertaining to a wide range of operating conditions are also needed from the system to achieve acceptable prediction accuracy. Availability of such data is scarce especially for complex or newly designed systems.

In contrast, model-based methods (or physics-based methods) use a physical model which describes the degradation behavior of the system to estimate the fault evolution trend. These methods require adequate knowledge of the system's life cycle, loading conditions, material properties and the physics of underlying failure mechanisms to predict the density function of the RUL. Availability of an accurate degradation model can aid in the precise prediction of failure progression and eventual prognosis. The commonly used model-based methods in literature are the Kalman filter-based methods such as Kalman filters (KF), extended Kalman filters (EKF) [11], unscented Kalman filters (UKF) [12] and particle filter-based methods such as standard particle filters (PF) [13], unscented particle filters (UPF) [14], regularized particle filters (RPF) [15] etc.

Bressel *et al.* [16] used an extended Kalman filter approach to predict the state of health and RUL of a proton exchange membrane fuel cell (PEMFC). A single empirical model

was deduced from the polarization curves and the Levenberg Marquardt (LM) algorithm was used to optimize the model parameters. The prognostic results obtained were accurate even for dynamic loading conditions. An extension of their work was then proposed by Zhang *et al.* [17] wherein the empirical model was replaced by a physics-based degradation model representing the relationship between the operating conditions and the degradation rate of the electro-chemical surface area in the PEMFC. An unscented Kalman filter-based framework which can handle the non-linearities in the system model was also proposed for health monitoring. Although Kalman filter based methods predict the RUL with good accuracy, noise in the system is always assumed to be Gaussian. Also, a precise initial state is required to achieve good prediction accuracy thus limiting its applicability to practical applications which mostly possess non-linear system dynamics with non-Gaussian noise embedded in it. Saha *et al.* [18] proposed an exponential empirical model describing the lithium-ion battery degradation behavior for each discharge cycle. A particle filter framework was again used to make predictions for the RUL for individual discharge cycles as well as for the entire lifecycle of the battery.

Particle filters (PF) are extensively used for the purpose of prognosis because of its ability to handle non-linear systems with non-Gaussian noise. Recent studies have shown that particle filters exhibit higher prediction accuracy over EKF, UKF, regression-based methods and non-linear least square methods etc. even when there are only few measurement data available from the system being monitored [19]–[21]. Even though physics-based methods can obtain accurate predictions, the mathematical model used in these methods are based on specific knowledge of the system under specific operating conditions. Uncertainty in the physical model or a phase-wise transition in the physics inhibits the quick application of PF for real-time scenarios where the component / system degradation dynamics is complicated and/or is not fully known.

Several attempts have been made to overcome the uncertainty in the damage propagation models used in filtering techniques-based RUL predictions. Some of the proposed models include one-term exponential model for Li-ion battery capacity degradation using spherical cubature particle filters [22], quadratic polynomial model [23], two-term exponential model [24] and ensemble model [25] etc. Although the above-mentioned models work well to predict the RUL of lithium-ion batteries, they are designed for devices which follow a *single* degradation behavior throughout the lifecycle of the device. Rolling element bearings for instance are used in harsh working environments and are subjected to rapid degradation over time. To assess the degradation of bearings, health indicators constructed from vibration signals are used. The bearing degradation process can be classified into two phases. The first phase comprises the normal working condition with constant rate of degradation whereas the second phase is where the bearing degrades exponentially. In such cases, the application of a single analytical model leads to

poor prediction accuracy as it is difficult to estimate or infer the time instant at which there is a transition of the degradation trend into the second phase. Knowledge of this transition / inflection point would be essential for taking adequate preventive actions.

Some of the very recent works have tried to address this complexity partially. Wang *et al.* [26] proposed a novel mixed effects model to analytically model the bearing degradation process. A joint posterior distribution was formulated based on the two mixed effect models and the RUL was predicted incorporating multiplicative errors and Brownian motion errors. Similarly, Banerjee *et al.* [27] proposed a two-stage degradation model based on the Paris law for the estimation of impact damage propagation in glass fiber reinforced polymers (GFRP). The authors further extended their work for prognostic study of matrix stiffness degradation of GFRP plates due to fatigue testing as well [28]. As the stiffness parameters were estimated using different nondestructive evaluation (NDE) techniques simultaneously, a multi-sensor particle filter framework was proposed. Since the physics behind each NDE technique is different, a joint likelihood function of the particles was proposed which dynamically updates the particle weight based on each individual sensor measurement. The authors however evaluated their proposed methodology only on a network of two sensors and the prediction error was found to be around 20%. Also, the authors did not consider the determination of the inflection point where the second mechanism starts to kick in. On the other hand, Diao *et al.* [29] proposed a new algorithm based on the slope-changing ratio of the tangent lines to determine the knee-point of the degradation curves in Li-ion batteries and suggested to use it as a degradation metric. However, they did not perform any prognostic study. Similarly, Cong *et al.* [30] proposed an improved unscented particle filter method to deduce the inflection point and Wang *et al.* [31] proposed a new piecewise degradation model for Li-ion batteries incorporating the battery regeneration phenomenon to eventually predict the remaining useful life.

In this work, we chose to work on nickel manganese cobalt oxide Li(NiMnCo)O_2 batteries (NMC) [32], which are known to exhibit a two-phase degradation trend, for prognostic study. The main contribution of this work may be summarized as follows. First, we propose a particle filter based online prognostic framework wherein a two-phase sequential degradation model is incorporated. Secondly, we use the error in battery capacity prediction as the criteria to identify the transition (inflection) point from one degradation mechanism to the other. Lastly, we compare the RUL predictions of the proposed framework with other commonly used capacity degradation models to validate the effectiveness of our piece-wise prognosis framework.

The remainder of the paper is organized as follows: Section II describes the experimental data used in this work followed by formulation of a piecewise capacity degradation model. Section III introduces the standard particle filter algorithm and Section IV provides a detailed explanation

of the proposed framework and also compares the prediction results between a piecewise model and other empirical models available in literature. The results indicate that the use of a piecewise model with inflection point does provide better results in terms of RUL prediction accuracy for the same computational load. Finally, Section V provides some concluding remarks and recommendations for further work.

II. CAPACITY DEGRADATION MODEL
A. CAPACITY MEASUREMENT
The aging behavior of the battery is heavily dependent on the battery material make-up. One of the commonly used batteries is the nickel manganese cobalt oxide Li(NiMnCo)O_2 one, in short, referred to as NMC. The NMC cells exhibit a concave degradation trend in comparison to other conventionally used batteries such as lithium iron phosphate (LFP) batteries which are convex. The capacity of the NMC cells steadily decreases in the initial cycles until it sharply falls beyond a certain inflection point as shown in Fig. 1. Yang *et al.* [33] performed accelerated aging experiments on NMC cells and in turn proposed a two-term capacity degradation model for the purpose of RUL estimation. The authors used four cylindrical NMC B18650CD cells composed of Li(NiMnCo)O_2 cathode and carbon anode with a rated capacity of 1.35 Ah.

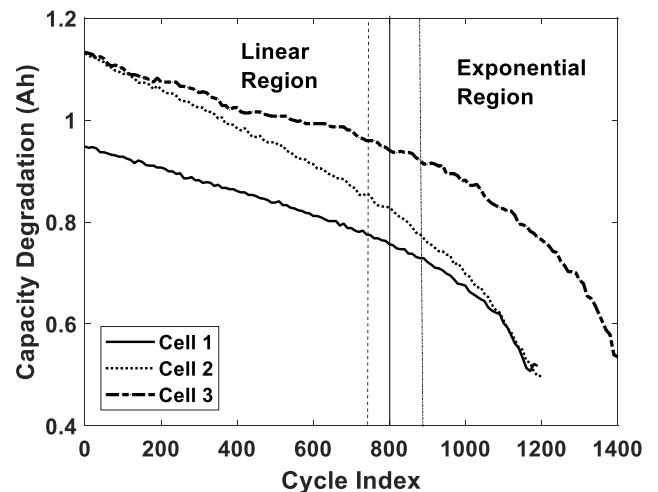**FIGURE 1.** The degradation curves of Li(NiMnCo)O_2 cells extracted from Ref [30], subject to accelerated aging experiments under ambient temperature conditions showing a two-phase degradation trend with the dotted lines representing the possible region where the degradation transition happens.

These four cells were repeatedly charged and discharged till failure using the constant current/constant voltage protocol at a constant current rate of 1.35 A. The cut-off voltages were 4V and 2.5V for each charge/discharge cycle, respectively. The cells were placed in a thermal chamber to sustain the ambient temperature at 25°C. The capacity degradation curves are shown in Fig. 1 above. We tested our algorithm using these capacity degradation data sets.

B. CAPACITY DEGRADATION MODEL FORMULATION

From Fig. 1, it is evident that the capacity degrades slowly in the initial few cycles, until the degradation rate becomes exponential beyond a time instant. The transition point from a slow linear degradation phase to an exponential degradation phase is termed as the inflection point. A piecewise degradation model is proposed here to analytically model the two-phase degradation trend with respect to the inflection point.

$$C_k = \begin{cases} (-a_k)x_k + b_k, & k \le \tau \\ c_k \exp(-d_k)x_k, & k > \tau \end{cases} \tag{1}$$

where C_k represents the estimated capacity of the battery, x_k is the current state and k is the cycle index. Parameters a_k and b_k represent the linear model parameters and c_k and d_k are the exponential model parameters. The battery is expected to follow a linear model till the inflection point, τ, after which it enters the exponential degradation phase.

III. PARTICLE FILTER FRAMEWORK

A. PARTICLE FILTER BASED PROGNOSIS

Particle filters are sequential Monte Carlo (SMC) methods predominantly used for solving state estimation problems. The particle filter algorithm is implemented based on Bayesian inference and the key idea is to represent the posterior probability density function (pdf) by a set of weighted samples called particles. These particle weights basically denote the discrete probability masses.

Particle filters works as a recursive Bayesian filter. The posterior distribution is approximated by a set of weighted particles which represent the state of the system. The posterior distribution at the current time instant is assumed to be the prior for the next time instant. When a new measurement data is available for prediction, the weights of the particles are updated according to a likelihood function to account for the new data point. These weights are resampled to improve the diversity among the particles and in turn the posterior distribution for the current time instant is deduced as shown in the schematic in Fig. 2. In a standard particle filter algorithm, the system state dynamics can be represented by a state-space model with the help of the following state equations.

$$x_k = f(x_{k-1}) + \upsilon_k \tag{2}$$
$$z_k = h(x_k) + \omega_k \tag{3}$$

where x_k denotes the state of the system and z_k denotes the output measurement data. *f(.)* denotes the state transition function which incorporates the incremental capacity degradation model (physics embedded) and *h(.)* denotes the measurement function. υ_k and ω_k represent the process and measurement noise, respectively. The particle filtering approach can be summarized in the following steps.

1) INITIALIZATION

At the $k = 1$ step, n samples of the state space model parameter values are drawn from the initial/prior distribution
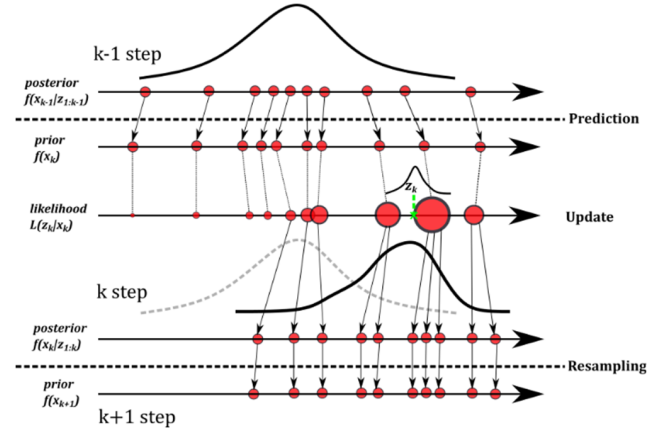

FIGURE 2. Schematic diagram of the standard particle filter framework showing the resampling of particles and the real-time update of state values with new data based on Bayesian inference.

where n represents the number of particles. In this work, n is assumed to be 1000.

2) STATE PREDICTION

Assume that the state x_k needs to be estimated based on the observations, $z_{0:k} = \{z_j, j = 0, \dots, k\}$, and the variables of the states follow a first order Markov process such that $p(x_k|x_{0:k-1}) = p(x_k|x_{k-1})$. Given the posterior distribution at the $(k\text{-}1)^{\text{th}}$ time instant, the prior distribution for the current time instant can be determined using the Chapman-Kolmogorov equation:

$$p(x_k|z_{0:k-1}) = \int p(x_k|x_{k-1})p(x_{k-1}|z_{0:k-1})dx_{k-1} \tag{4}$$

3) UPDATING

When a new measurement data, z_k, at time k is available for prediction, the prior distribution in Eqn. (4) is modified to obtain the posterior distribution of x_k through the following equations:

$$p(x_k|z_{0:k}) = \frac{p(z_k|x_k)p(x_k|z_{0:k})}{p(z_k|z_{0:k-1})} \tag{5}$$

$$p(z_k|z_{0:k-1}) = \int p(z_k|x_k)p(x_k|z_{0:k-1})dx_k \tag{6}$$

In practical applications, solving multidimensional integrals required in Eqns. (4) and (6) are difficult. Therefore, particle filter algorithm uses a set of weighted particles to represent the posterior distribution. The particles and their associated weights are represented as $\{w_k^i\}_{i=1}^{Ns}$ where N_s is the total number of random particles and the posterior distribution can thus be approximated as

$$p(x_k|z_{1:k}) \approx \sum_{i=1}^{Ns} \widetilde{w}_k^i \delta(x_k - x_k^i) \tag{7}$$

where δ is the Dirac delta function and $\widetilde{w}_k^i$ is the normalized weight of the particles, i.e.,

$$\widetilde{w}_k^i = \frac{w_k^i}{\sum_{i=1}^{Ns} w_k^i} \tag{8}$$

The weights of the particles are recursively updated to estimate the variables of the state.

B. RUL PREDICTION BASED ON THE PROPOSED MODEL

The incremental capacity degradation according to the proposed piecewise model (Eqn. (1)) can now be rewritten as:

$$x_k = \begin{cases} (-a_k \Delta t)x_{k-1} + b_k, & k \leq \tau \\ c_k \exp(-d_k \Delta t)x_{k-1}, & k > \tau \end{cases} \quad (9)$$

where x_k and x_{k-1} are the estimated battery capacity at the current and previous time instants, respectively. The remaining useful life of the battery at the current cycle k can be estimated by:

$$RUL_k = EOL - k \quad (10)$$

where EOL refers to the predicted end of life of the battery.

IV. RESULTS AND DISCUSSION

A. RUL ESTIMATION WITH ONE EXPONENTIAL TERM MODEL

The most commonly used lithium-ion battery degradation models are the polynomial model and the single-term exponential model. In this section, a single-term exponential model is first used to predict the RUL of the NMC cells. An online prognostic investigation is performed wherein 400 cycles of data are assumed to be available for prediction. The curve fitting tool is used to estimate the model parameters from the available measurement data. The incremental degradation model based on an exponential trend can be represented as follows:

$$x_k = c_k \exp(-d_k \Delta t)x_{k-1} \quad (11)$$

For every new data point available for prediction, the particle filter algorithm is used to estimate the model parameters. Number of particles is chosen to be 1000 and the mean value of the predictions at each time instant is considered as the estimated battery capacity. The degradation prediction traces for the NMC battery labeled "Cell-2" are shown in Fig. 3. The model can capture the initial linear phase of degradation with good accuracy whereas during the later exponential degradation phase, the predictions are completely diverging away from the true value. It is evident that the prediction traces for the single-term exponential model are almost linear throughout and it is unable to capture the two-phase concave degradation trend. Also, the model fails to capture the inflection point and hence is unable to represent the non-linearity introduced by the change in battery material physics.

B. PROPOSED ONLINE PROGNOSIS FRAMEWORK

Based on the prediction results of the single-term exponential model, it is clear that a new prognostic framework is certainly needed to capture the inflection point and in turn switch the degradation model as per Eqn. (9). In our proposed framework, the percentage prediction error between the estimated battery capacity and true value is considered as the deciding factor for determining the inflection point.
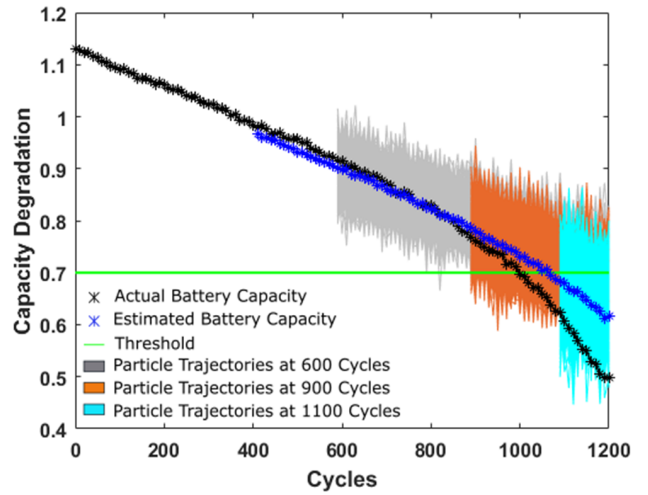

FIGURE 3. The prediction curves for a single term exponential model with prediction starting point at 400 Cycles. The grey, orange and cyan traces represent the particle trajectories at 600, 900 and 1100 cycles respectively for 1000 particles.

The proposed framework is illustrated in detail through a flowchart in Fig. 4. The prognostic framework consists of two stages: parameter initialization and prognosis. We have assumed that the battery's aging follows a linear trend initially in the slow degradation phase followed by an exponential trend. In the initial stage, available measurement data is fitted into a linear model and the fitting parameters are fed into the particle filter algorithm as initial parameters.

Battery capacity for the $(k+1)^{th}$ cycle is estimated based on Eqn. (9). The percentage error between true value and estimated battery capacity at the $(k+1)^{th}$ time instant (equivalent to cycles) is evaluated. The time instant at which the estimated capacity starts to diverge away from the true value i.e. the time instant at which error value increases by more than 3% is defined to be the inflection point. The capacity degradation model switches based on the inflection point and a step function is used to represent it as shown in Fig. 5. The error threshold is set to be 3% based on prediction results of the single-term exponential model. At this stage, it can be inferred that the battery has started to deteriorate rapidly. Hence, predictions beyond the inflection point are done based on the exponential model. In order to capture the non-linearity in the concave degradation pattern, the initial parameter guess values for the model parameters c_k and d_k are obtained by fitting the measurement data till the current time instant into an exponential model. The curve fitting values are in turn used in the particle filter algorithm. However, it is necessary to choose optimum parameter limits so that range of parameters is not too narrow or too wide as this would cause a failure to converge to true value. Thus, a scalar multiplier 'm' is introduced for this purpose such that:

$$Upperbound = m * Lowerbound \quad (12)$$

The optimum value for the scalar multiplier 'm' is set as 10 in this work based on trial and error. The values much lower or
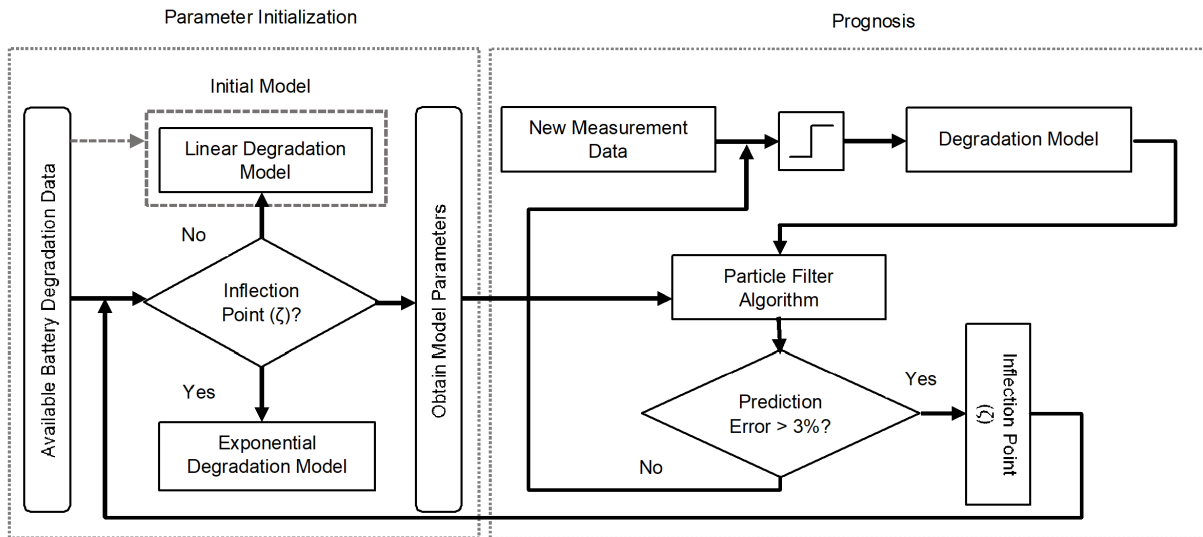
FIGURE 4. The proposed prognostic framework to determine the inflection point.
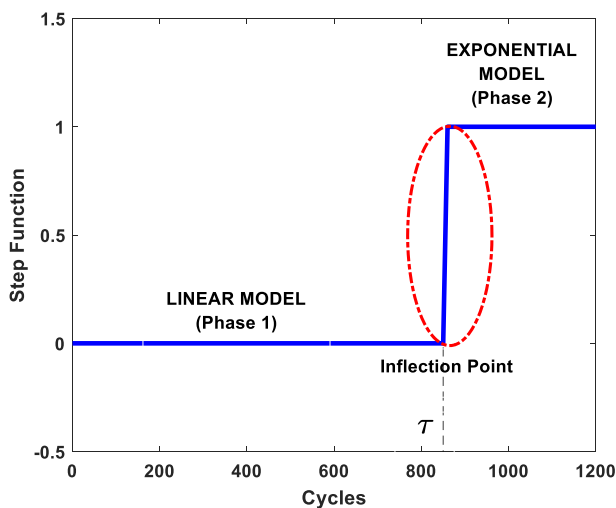

FIGURE 5. The step function describing the point of inflection (abrupt change of degradation mechanism in our state space model) based on the error threshold value.

higher than 10 fail to capture the degradation pattern and as a result, the prediction results are either much lower than the true value or highly noisy, respectively. It is logical to expect an optimum value of m to exist, as very narrow or very wide range of parameter values can compromise the prediction accuracy in any Bayesian analysis.

C. RUL ESTIMATION WITH THE PROPOSED PIECEWISE MODEL

Prognosis based on the proposed framework is carried out on the NMC battery data shown in Fig. 1 and the prediction results are reported in this section. Initial distribution of the model parameters was obtained from the curve fitting results

of the first 400 cycles of measurement data available for prediction, as already mentioned earlier. The black datapoints in Fig. 6a depict the actual battery data and the blue datapoints denote the mean values of the estimated capacity at every $(k+1)^{th}$ time instant. Here, the number of particles was arbitrarily chosen to be 1000.

The prediction results till 870 cycles (considering the linear degradation model) are in good agreement with the true value. Moreover, the width of the predicted confidence interval is small denoting good prediction accuracy. The confidence interval and particle trajectories for the prediction results at 600 cycles is depicted by the white and gray lines in Fig. 6a respectively. The prediction error reaches 4.2 % at the 880th cycle and hence the inflection point is estimated to occur at the 870th cycle. Now, the step function in the proposed framework switches the capacity degradation model to an exponential function. Even though prediction error is slightly higher in the exponential region compared to the linear region, the model manages to capture the degradation trend. The wider confidence intervals at 900 and 1100 cycles shown by the orange and cyan lines in Fig. 6a may be attributed to the uncertainty introduced by the scalar multiplier for estimating the model parameters.

To validate the robustness of the proposed framework, a 50dB additive Gaussian white noise is added to the measurement data and also to every new measurement data as well. The error threshold and the scalar multiplier are retained to be 3% and $m = 10$, respectively. The prediction results for the noisy signal are shown in Fig. 6b. The inflection point was estimated to be at 860 cycles which is in good agreement to that of the clean signal. It is evident from the prediction results that the impact of noise in measurement data is minimal in the proposed prognostic framework and prediction accuracy continues to be good.
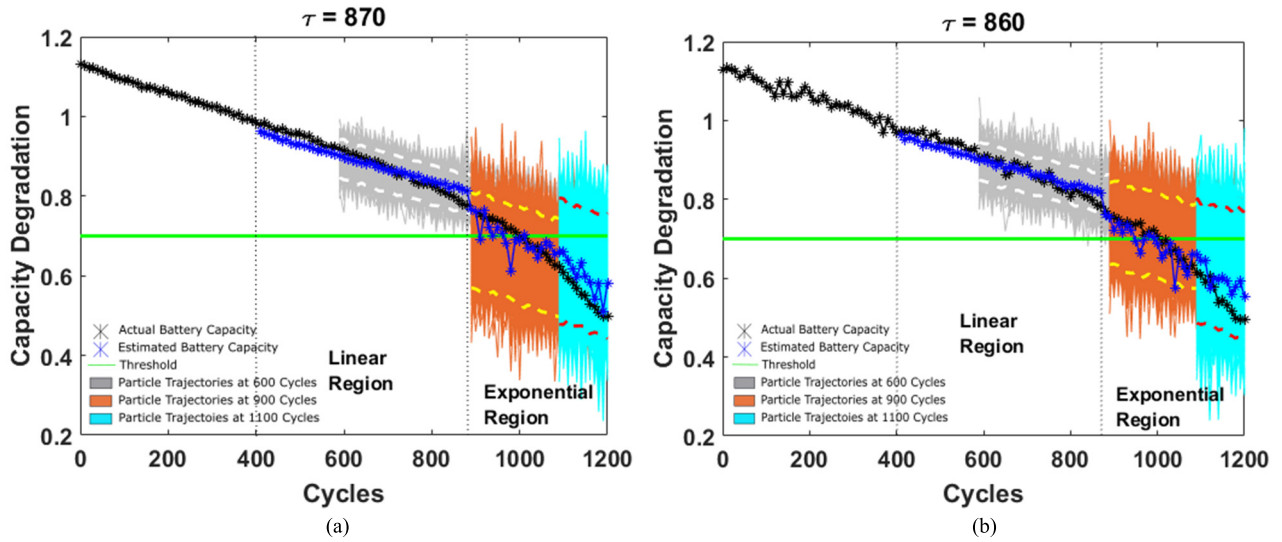
FIGURE 6. The prediction curves for the proposed piecewise model with prediction starting point at 400 Cycles for (a) clean data, (b) 50dB noisy data. The grey, orange and cyan traces represent the particle trajectories at 600, 900 and 1100 cycles respectively for 1000 particles.

D. PERFORMANCE METRICES

The computational load is a critical factor for online prognosis applications. Since particle filter algorithms are computationally intensive, it is vital to take the computational time as an important prognostic metric. The computation time depends on the number of particles chosen for achieving good prediction accuracy. Thus, the choice of number of particles is largely a comprise between accuracy and time.

The computational time for all three models while using 1000 and 5000 particles are listed in Table 1. The prediction error is yet another prognostic metric used in this study. It is evident from the error evolution plot in Fig. 7 that the prediction error (computed using the absolute error (AE) metric) for the single term exponential model starts to increase drastically beyond the inflection point. Also, the prediction error for the piecewise model is within 10% barring a few outliers. As always, the desired accuracy of RUL prediction involves a compromise with the computational load and this compromise can vary depending on the context and time scale of usage of the framework in a real-time prognostic application.

TABLE 1. Variation of computation time with number of particles.

Model	Computational Time (secs)	
	1000 Particles	5000 Particles
Single-Term Model	75.70405	386.6756
Piecewise Model (Clean)	67.71403	357.1022
Piecewise Model (50dB Noise)	69.21182	379.656

Additionally, we have compared the performance of our proposed framework to that of the results published by
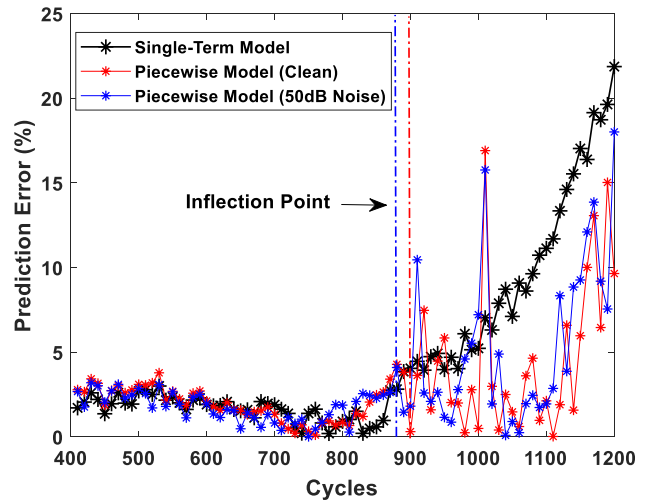

FIGURE 7. Comparison of single-term exponential model with the proposed piecewise model for a clean and noisy signal using prediction error (based on the AE values) as performance metric.

Yang *et al.* in Ref. [33], below in Table 2. The authors in Ref. [33] had used a two-term logarithmic model to capture the two-phase degradation of the NMC batteries and compared the results with one-term exponential model (OE), quadratic polynomial model (QP) and two-term exponential model (TE). The results for the RMSE values for different degradation models along with our proposed methodology for all the three cells are listed in Table 2. The results clearly indicate that our proposed method outperforms the OE and QP models. However, the RMSE values obtained from the TE model are very close to that of our proposed method. However, it is worth noting that the TE model could not capture the inflection point position precisely despite the fact that the degradation model parameters were deduced specifically for

TABLE 2. Comparison of RMSE values for selected battery degradation models.

Cell No.	Model OE Ref. [33]	Model QP Ref. [33]	Model TE Ref. [33]	Proposed Method (This Study)
Cell-1	2.9×10^{-2}	8.9×10^{-3}	2.4×10^{-3}	2.69×10^{-3}
Cell-2	1.8×10^{-2}	7.7×10^{-3}	2.6×10^{-3}	2.49×10^{-3}
Cell-3	3.4×10^{-2}	1.54×10^{-2}	1.5×10^{-3}	3.7×10^{-3}

each cell under consideration. Hence, the proposed method outperforms other mainstream models in literature for RUL prediction of batteries with two-phase degradation trends and also successfully estimates the inflection point even for gradual transitions between different degradation mechanisms.

V. CONCLUSION

NMC batteries exhibit a two-phase concave degradation pattern due to complexity in the battery material physics compared to conventional lithium-ion batteries. We have proposed a piecewise model to capture the two-phase degradation trend incorporating a linear and an exponential model, thereby enabling improved battery capacity degradation tracing and remaining useful life prediction. The proposed framework may be suitable for online prognosis of slowly degrading systems and has the ability to explicitly and automatically estimate the time instant at which the inflection from one mechanism to the other occurs.

The prediction results are compared with a single-term exponential model extensively used in literature for battery prognosis. The results clearly indicate that the proposed model outperforms the single-term model. The robustness of the proposed framework was validated by adding 50dB additive Gaussian white noise to the measurement data. Also, the impact of the number of particles on the computational load of the algorithm was also explored. Higher number of particles largely increases the computational load without any decrease in the prediction error. Hence, selection of 1000 particles were found to be ideal for the proposed framework. The percentage prediction error (using the AE values) was another performance metric used in this work. The error value rapidly increases after the inflection point when the battery starts to degrade exponentially for the single-term model. However, the proposed piecewise model considerably reduces the error in the second phase of degradation. We intend to extend our proposed model in future to improve the prediction accuracy wherein we estimate the region of inflection by replacing the step function with a sigmoid function as the transition region in general is not digital; it should be a fuzzy region rather than a single point in time and that the change in degradation physics happens gradually in reality. Also, we intend to test the applicability of our proposed method for case studies

relating to crack propagation in composite materials as well where such two-phase mechanisms are prevalent.

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