Lithium-ion battery ageing prediction in real time using Genetic Algorithm in MATLAB

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Abstract. Highly accurate State-of-Health(SoH) assessment in lithium-ion based cells is exceptionally difficult due to the nonlinear exhibits of batteries and the complex application environment in hybrid electric vehicles (HEVs) and electric vehicles (EVs), primarily variations in temperature conditions.TheStateofCharge(SOC)conditions were calculated using the extended Kalman filter algorithmin this paper using an analogous circuit model with experimental data. A two-layer feedforward neural network (FFNN) with sigmoid function and Levenberg-Marquardt training algorithm choice was used to optimize the estimated performance. For a constant temperature of 35°C, plot findings were cross-correlated with various SOC conditions using electrochemical impedance spectroscopy (EIS). The developedEKFestimationmodelisevaluatedcurrentprofiles to compute the change in voltage for estimating the battery's SOH. The developed EKF estimation model was analyzed current profiles to compute the change in voltage for estimating the battery's SOH. A hardware-in-loop (HIL) test bench using the OPAL-RT tool is designed for the real-time and heuristic of the developed EKF estimation model to evaluate current profiles to compute the change in voltage estimation of the battery's SOH.

Keywords: SoH, HEVs, Evs, FFNN, SOC, OPAL-RT.

1 Introduction

The battery degradation is a crucial factor that impacts battery performance while using management of energy thermal, charge/discharge, and cell balancing managements [1-3].For the most part, the age of the batteries in electric cars (EVs) can result in a 20% loss in performance. Their internal resistances increased by 100 percent and their usable capacities increased by 100 percent [8,9]. Batteries can also degrade in certain unusual circumstances. Lead to integrated energy system failure and safety concerns [5-8].

The condition of one's health (SOH) was investigated. However, using only current SOH data for power scheduling and energy management is insufficient since most users want to know how long a battery will last [10,11]. Users' concerns about the battery's lifetime and protection can be alleviated by knowing how long it has left to serve [15,16]. Predicting battery capacity depletion will also assist in the optimization of multidisciplinary energy activities, as well as the efficiency and dependability of energy systems [17].

As a result, for efficient energy management, anticipating the battery's future power ageing patterns is important. One of the simplest ways for determining the battery energy degradation trajectory is to conduct direct experiments under load certain conditions. This approach, on the other hand, usually necessitates a months-long or even years-long testing

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phase. After the testing, the batteries will be significantly depleted and useless. As a result, rather than being used in real-time applications, this approach is frequently used in the laboratory to generate ageing trajectories with a reference.

The first step in generating credible online battery ageing forecasts is to get current degradation trends. The battery deterioration pattern is then extracted using multiple methods, allowing future projections to be created by appropriately extending the battery ageing trend. Using data driven techniques such as time series analysis, data-fitting techniques, and sensor fusion approaches with optimal estimation are three sorts of algorithms extensively used by the researchers [18-22].

The battery's SOH aging due to calendar life and cycle lifefor a factor of M degradation (SOH) is considered to have certain underlying correlations with the historical SOHs collected from the previous N steps for time-series dependent predictions Artificial intelligence (AI) approaches such as neural networks [21], support vector machines (SVM) [22], and relevant vector machines (RVM) [23] have been successfully used by the researchers training the experimental data to develop a robust BMS system design . The time-series analysis information provides battery ageing effects with training, testing and validation approaches from the experimental data.With modern computational facility the above techniques enhance the robust BMS design with feasible cost.

After obtaining battery history ageing data analysis, the essential chartingamong battery SOH with charge/discharge cycles is established by plotting and fitting the datasets into a realistic deterioration model for data-fitting dependent prediction algorithms. The battery degradation level may therefore be projected over time using the verified model. Physics-based model approaches, which custom many partial differential equations (PDE) to clearly describe battery degradationbehaviours, are a good fit here [24-25].

While simulations may be used to investigate the complex electrochemical dynamics of battery ageing, the physics models required are often memory-intensive and complex, making real-time ageing trajectory predictions prohibitively expensive [26]. The major analysis are carried out using linear, single exponential, dual exponential and polynomial are the suitable methods for the realistic/ true estimation.

The most common method adopted in BMS is empirical model fitting-based estimationfor their simplicity and ease of implementation (BMS).

A basic empirical model, on the other hand, is susceptible to noise, particularly when training data is few. The parameters of an ageing model are considered state variables in filter-based prediction approaches, and they are detected online using state observers or filters. The noise-sensitivity of these algorithms is lowered when compared to the empirical prediction-based technique when sophisticated observers or filters are used. Due to hardware implementation feasibility recursive filtering approaches are more suitable for real-time usages.

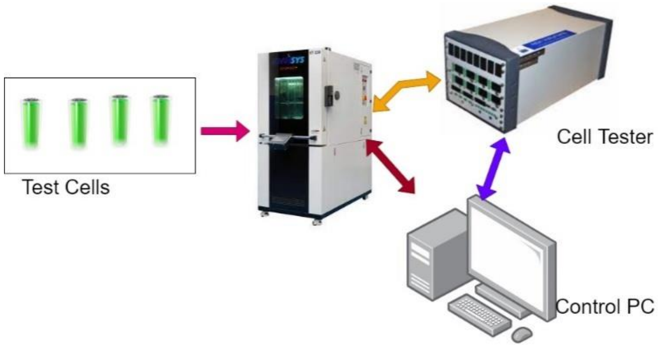

Fig.1. Test battery workbench architecture

Consequently, the optimal state estimation techniques filter-based prediction and correction is is one of the highly adopted by the researchers in battery deterioration analysis. Particularly in non-linear filtering methods which include the Luenberger observer, Kalman filtering, and particle filter (PF)-based algorithms. PF is unique among these algorithms in that it can solve non-linear and non-Gaussian problems, and it is frequently employed in health prognosis. The filtering findings of PF, like other current observers, are highly impacted by the original meaning, and they are more delicate to fresh data sets than the previous. These techniques are completed in six-steps each three with prediction(measurement) and correction with error covariances.

Predicting the ageing trajectory of batteries, according to the study, is technically difficult for at least two reasons.To begin with, battery deterioration is a dynamic nonlinear process that involves interlinked physical and chemical processes. A holistic view of this process is challenging to generate and compute the complexity, and if a reduced empirical model is used, the local ageing trend generated.The entire trend of long-term battery deterioration may not be fully represented by the inadequate historical data.

Low-cost sensors in the BMS, for example, might create substantial noise, as could unpredictable climatic condition varies with respect to time [38]. This is a completely diverse scenario than when exact lab procedures are employed [39]. When defining a non-linear model using inadequate trained data sets and extensive noise, it is challenging to assure optimal curve fit correctness. Prediction ageing trajectories might vary substantially depending on the amount of the training data utilized when the two problems are present. From the user's standpoint, a shaky forecast outcomes may raise battery life uncertainty, which must be avoided.

The goal of this work is to improve the efficiency of battery ageing prediction trajectory of effective energy management and control by proposing a base gradient-correct optimal filtering using genetic algorithm approaches. A gradient-based estimator improves the development of each particle within the context of PF, resulting in better tracking accuracy for the particles. In order to compel that local identification yield to closely match with global result, the model-based normalisation is also presented. minimizing the algorithm's susceptibility to local ageing trajectory action.

The parameters of an ageing model are considered state variables in filter-based prediction approaches, and they are detected online using state observers. When compared to the empirical model-based prediction, sensitivity noise of these algorithms reduces when sophisticated filters opted. Filtering algorithm techniques-based methods is more suited in real-time applications with necessary computations using recursive manner.

Because of its mechanism-free characteristics, the proposed GA technique may easily be applied to a variety of battery types for accurate ageing trajectory prediction and energy management.

The remaining part of the paper discussion are: The battery ageing data sets that were used are described in Section 2. Section 3 then goes through the fundamentals of the conventional particle filter, using updated gradient prediction procedure, with the proposed GA algorithmappraoch. The remaining two benchmarks, as well as the algorithm assessment criteria, are defined in Section 4, discuses about the experimental data analysis. Finally, conclusion was made in section 5.

2 Experimental Design

Four distinct battery ageing data sets were obtained for this analysis to demonstrate with feasible battery ageing estimation approach. All the data setsadditive with the cyclic ageing data of four battery cells.

NASA has also picked a widely used ageing data standard to evaluate the suggested approach (see Ref. [44] for details).

The energy source voltage measuring range of this tester is performed with the voltage source of 5V, and measurement current varies with band of 10A. Ambient temperature maintained to 25 degrees, and the voltage and current measurements are accurate to 0.1 percent tolerances.

. %% Initialize Actual ModelParameters

R_plusActual = 0.1;

TABLE – 1 Battery Data

Battery type	NASA			
	#05	*#06*	*#07*	*#18*
Rated capacity (mAh)	2000	2000	2000	2000
Current-rate (Charge/Discharge)	0.85C/1C	0.85C /1C	0.85C /1C	0.85C /1C
Cut-off current	0.15C	0.015C	0.015C	0.015C
Cut-off voltage: Charge	4.23V	4.2V	4.2V	4.2V
Cut-off voltage: Discharge	2.7V	2.55 V	2.42	2.35

The CCCV profile is applied to fully charge test cells during each working phase of these three batteries, followed by a CC (constant current) profile to completelyempty the cells under the cyclic ageing conditions.

During cyclic ageing tests, all relevant current and voltage data is continuously collected. By integrating the current throughout each loop, the discharging capacity is determined. It's worth mentioning that all of these studies were conducted at room temperature without the use of precise temperature control, making the procedures used to account for the effects of the heard sounds far more difficult. Table 1 summarises the further information of test data sets, power rating, C-rate, lower cut-off current and voltages, and the number of testing cycles.Due to variations in chemical compositions and operating conditions, the lifespan of these batteries is predicted to vary greatly.

3 Methodology

The goal of this part is to compare and motivate different algorithms by starting with a specification of a typical GA-multi-object algorithm. After that, the enhanced gradient-corrector-based Genetic Algorithm is described in greater depth.

Proposed GA algorithm.

1. %% function ... [SOCActual,TerminalVoltageActual]= Experimental_BatteryModel_NASA_18_2(AgedCell_I, ATime)
2. %% Define Battery Model Parameters
   R_minusActual = 0.1;
   K_0 =3;
   K_1 =0.01;
   K_2 =0.01;
   K_3 =0.01;
   K_4 =0.01;
4. %% Run Battery MActualodelSOCActual = []; TerminalVoltageActual = []; AgedCell_Ik = length(Current); for k = 1 : 1 :AgedCell_Ik
5. % SOCUpdate
   U =Current(k);
   CoffB3 = -(eta * DeltaT / Cn); SOC = SOC + (CoffB3 *U);
6. %% Run Updated Model if Current(k) >= 0 TerminalVoltage =K0

```
- (R_plusActual * Current(k))
-K1/SOC ...
-K2*SOC ...
+ K3*log(SOC) ...
+ K4*log(1-SOC) ;
else
TerminalVoltage =K0 ...
- (R_minusActual * Current(k))
-K1/SOC ...
-K2*SOC ...
+ K3*log(SOC) ...
+ K4*log(1-SOC) ;
```

Current	= AgedCell_I;	end
DeltaT	= 0.1;	TerminalVoltageActual=[TerminalVoltageActual;
Cn	= 5.4 * 3600;	TerminalVoltage];
eta	= 1;	SOCActual = [SOCActual;SOC];
SOC	= 0.9;	end

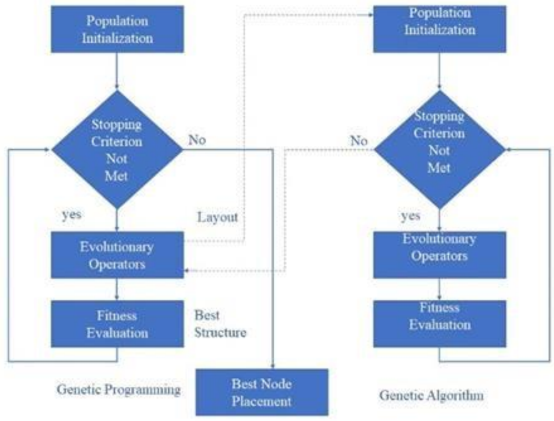

Fig. 2. The proposed GA algorithm Flow chart

4 Experimentalverification And Results

In this section, the suggested method's efficacy is thoroughly tested through trials. Benchmarking GA methods for comparison are implemented first in Fig. 1, followed by parameter settings in graph, and lastly the results in Fig. 7.

A. Algorithm assessment benchmarks and criteria:

Genetic algorithms are proposed in this paper. First, the traditional GA is chosen as benchmarking algorithm 1 since its fundamental structure is close to that of the proposed GA. The battery deterioration model would be constructed using the offline nonlinear fitting techniques provided in MATLAB for this algorithm, based on the entire ageing data.

B. Experimental results:

The four battery data sets are trained in a genetic algorithm, and a graph is displayed between voltage, current, and temperature versus off springs in the genetic algorithm. The experiment is calculated in MATLAB for 200 iterations. From the results the degradation of the battery life can be identified based on the cycles undergone. It clearly shows that as the cycle time increases the battery life degrades.

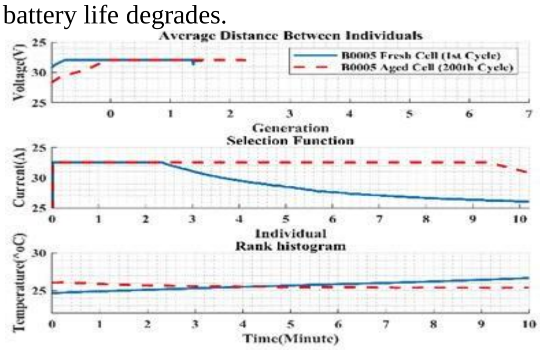

Fig. 3. Comparison of Fresh & Aged Cell for 200 Cycles Using Genetic Algorithm [B0005]

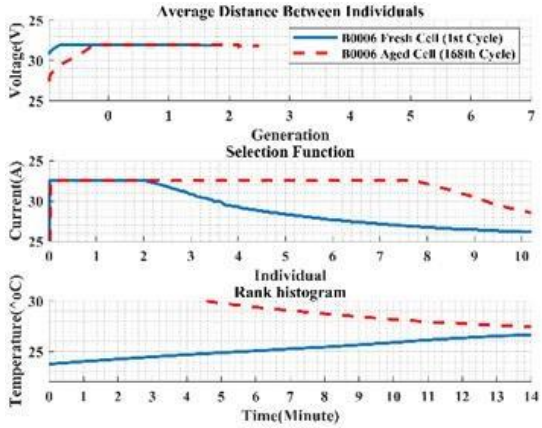

Fig. 4. Comparison of Fresh & Aged Cell for 200 Cycles Using Genetic Algorithm[B0006]

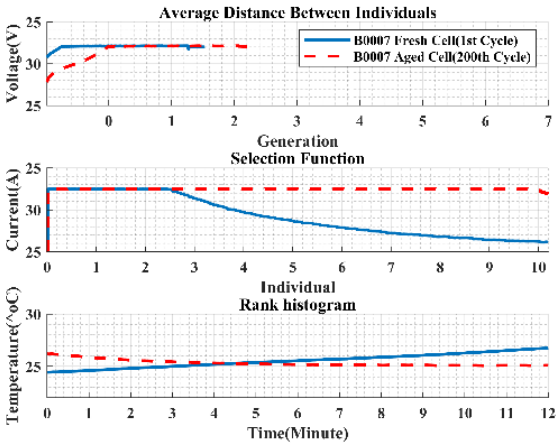

Fig. 5. Comparison of Fresh & Aged Cell for 200 Cycles Using Genetic Algorithm[B0007]

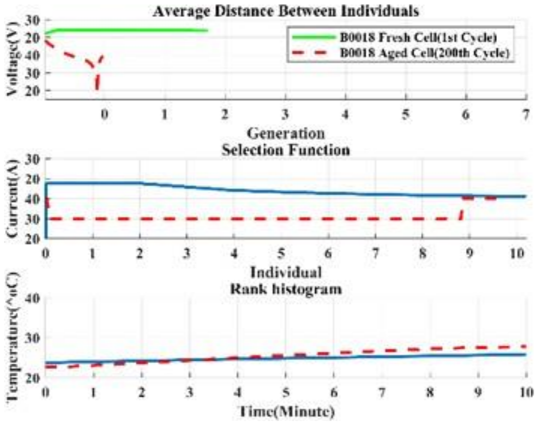

Fig. 6. Comparison of Fresh & Aged Cell for 200 Cycles Using Genetic Algorithm[B0018]

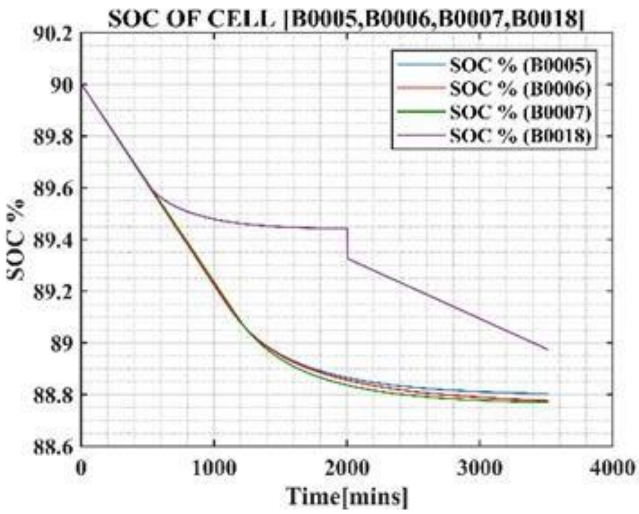

Fig. 7. State of Charge (SOC) of Batteries With respect to time

The above graph shows that at given load the battery can withstand about 3500 minutes. It compares of four battery Cell 1-B0005, Cell 2- B0006, Cell 3- B0007, Cell 4-B0018.

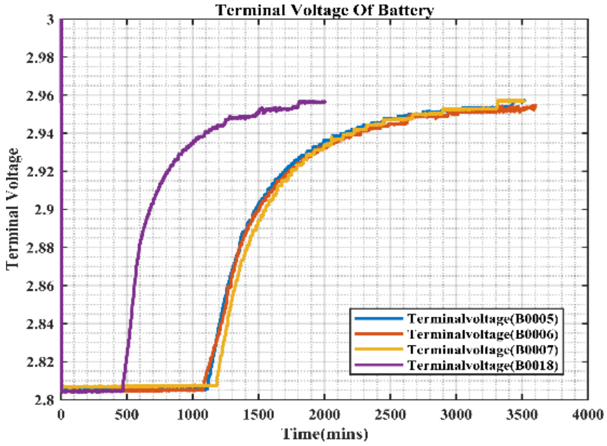

Fig. 8. Terminal Voltage of Four Batteries [B0005, B0006, B0007, B0018] with respect to Time.

Conclusions

In applications such as power scheduling, energy management, and temperature control, battery ageing prediction is critical. This research proposes a hybrid approach for predicting ageing that is based on a model-oriented genetic algorithm.

The tested profile pattern of Li-ion cells in terms of managing energy efficiency is the prime factor to control for minimal aging. Following are the most important elements in the development of technical innovations: To improve GA's tracking capabilities, a gradient-correction-particle filter might be created first. bettered Second, a model-based regulatory technique will be used. The algorithm sensitivein ageing curve's in processed activity can be significantly shortened. Aside from the frequently used RMSE, criterion known as SDE utilized to assess the accuracy of computed correction findings.

Comprehensive assessments with two other studies and analysis with benchmarkingcategorized with extended experimental tests with opted Li-ion cells yielded with the following quantitative conclusions, includes:

- ❖ The recommended GA would obtain a high prediction accuracy when 40 percent ageing data is used for model training, including measurement noise (RMSE lesser than 1.75 %).
- ❖ For energy control, GA may provide with decent estimation accuracy of RMSE 1.86 % while only requiring 10% of the training data and an acceptable base model.
- ❖ The SDE of the recommended approach is 32% lower than that of benchmark 1, suggesting that the fundamental model-oriented GA algorithm produces more consistent predictions

This is the first time we've seen a model regularisation technique combined with enhanced GA to handle battery ageing profile predictions. The described approach might be used to various battery ageing estimates for optimal energy management applied the proper data sets. To enhance our thoughtful of battery ageing mechanisms.The lifespan accuracy prediction will beconduct more research into battery aging with suitable alternative energy storage materials.

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