Evaluation of Features with Changing Effectiveness for Prognostics

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Abstract

Feature evaluation is crucial to identify the best features and to achieve high accuracy in diagnostics and prognostics. Feature evaluation for prognostics is a developing research area with several publications in recent years. Most, if not all, of existing methods to evaluate features for prognostics base on the feature changes in the whole life of the system under observation. In other words, feature values collected throughout the failure degradation are analyzed to create a goodness value for the feature. In reality, the goodness of the features may change during the failure progression. A feature may be good representative of failure progression in the initial phase but not in the final phases, or vice versa. This paper presents dynamic nature of representation capabilities of features throughout the failure degradation and proposes a novel approach to evaluate the features considering their dynamic nature. Proposed approach involves feature segmentation based on their representation capabilities and feature fusion utilizing the segmented evaluations. The presented approach has been applied in simulated and real degradation datasets. Real degradation dataset were obtained from accelerated aging tests of Li-ion batteries in the lab environment. The results from both datasets show that dynamic feature evaluation improves SoH estimation accuracy.

1. Introduction

Diagnostics and Prognostics are the major steps in Prognostics and Health Management (PHM) (Zhang & Lee 2011)(Camci & Chinnam 2005). Diagnostics is the process of identification of existing failures with its severity and/or location. Diagnostics is a classification or clustering problem in nature depending on the availability of labeled data. On the other hand, Prognostics is the process of identification of Remaining Useful Life (RUL) of the system or component under observation given its current health status. Prognostics is a forecasting problem that makes it more challenging due to many uncertainties involved in failure progression.

The sensory data and features extracted from them play crucial role in the accuracy of prognostics. None of the computational tools may extract the failure progression if it is not hidden in the features. The number of potential features that can be extracted from sensory data is huge with different effectiveness levels. Evaluation and fusion of the features that represent the failure progression well is the focus of this paper for the purpose of estimating RUL.

Feature evaluation and selection in diagnostics have been studied in the literature extensively. Researchers have started publishing articles about evaluation of features for prognostics in recent years. However, none of these work addresses the features' dynamic representation capability of failure progression. Features may represent the failure progression with different effectiveness throughout the failure progression or life of the component/system. A feature that does not represent the failure progression in the initial phase of the failure may represent the progression fully in the final phases. In contrary a feature that represents the failure progression perfectly in the initial phase may not represent the progression in the final phases. Thus, evaluation of feature effectiveness based on the full life of the component or system may be misleading. It is possible to use different features to measure the failure progression in different phases of the component or system life. This paper aims to fill this gap in the literature by presenting a dynamic feature evaluation algorithm and dynamic sensor fusion for prognostics.

The organization of the paper is as follows: Section II gives the literature review, Section III discusses the presented method for dynamic feature evaluation and fusion. Section IV presents the results obtained by the presented method on simulated and real data obtained from Li-ion batteries. The paper is concluded with Section V.

2. LITERATURE REVIEW

Measuring the effectiveness of features for diagnostics has been studied extensively (Hannah Inbarani et al. 2015), (Cecille et al. 2015), (Lamraoui et al. 2015), (Guana et al. 2014; Mwangi et al. 214AD). These studies can be categorized in two groups: non-transformed and transformed analysis (Mwangi et al. 214AD). In the former one, the features are evaluated as they are without converting them into another form. Evaluation can be performed by individual or combined analysis of features. The major disadvantage of this approach is the requirement of ignoring unselected features and not benefiting from the features that received low grade in the evaluation.

In the latter group, the features are converted into a different form in such a way that all features contribute to the new formatted features. The selection is performed based on the transformed features. In such a transformation, low graded features may also be contributed partially in the selected transformed features (Tianzhen et al. 2015). Principal component analysis (PCA) and independent component analysis (ICA) are two examples of this approach (Tianzhen et al. 2015; Z et al. 2011). PCA transforms n features into n new features, each of which is obtained with the contribution of old features based on their variance. The new features are ranked from the ones that hold most information to least information. Thus, the features with least information can be dropped from the analysis leading to reduced number of features. ICA on the other hand performs the transformation based on the independence of features.

Dynamic nature of the features' effectiveness has been studied for diagnostics in the literature. A feature may not be effective in the beginning for diagnostics, but become effective after the failure degradation reaches to a point. Online PCA has been developed to be able to handle the dynamic nature of the problem into account for classification (Honeine 2012).

Even though there has been extensive work on feature evaluation for diagnostics, this is not true for Prognostics (Camci et al. 2013).. The nature of the problem in Prognostics is totally different from diagnostics. Thus the methods used in diagnostics for feature evaluation cannot be used for Prognostics.

First study performed in feature evaluation for Prognostics has been published in 2013. This paper presents a method that quantifies the monotonicity of the trend in the features by dividing them into windows (Camci et al. 2013).. The data in consecutive windows have been analyzed to understand the existence of a change between data in windows. The change in all windows are quantified to measure overall monotonicity of the feature.

Genetic algorithm has been used to generate a formula to calculate a new feature that represents the failure progression using existing features (Linxia 2014). GA selects features among a feature pool and operators from math operations pool. The resultant formula has been evaluated using its effectiveness in representing the failure progression.

Entropy based sensor selection method is proposed in (Liu et al. 2015) for prognostics. This method quantifies the trend representing the degradation for given sensory dataset and entropy is used to represent the uncertainty within the data. Trigonometric functions and their cumulative transformation have been used to extract monotonic features. The goodness of the features for prognostics has been quantified by analysis of monotonicity and trendability (Javed et al. 2015). Monotonicity is the continuous increasing or decreasing nature of the feature and quantified as the sum of positive and negative derivatives. Trendability is basically defined as the correlation of a feature with time.

The structure of the data may change as a result of the feature selection due removed features. This change has been controlled through preserving the local and global structure of the data in order to achieve effective feature selection (Wang et al. 2014)(Peng et al. 2015). Feature selection

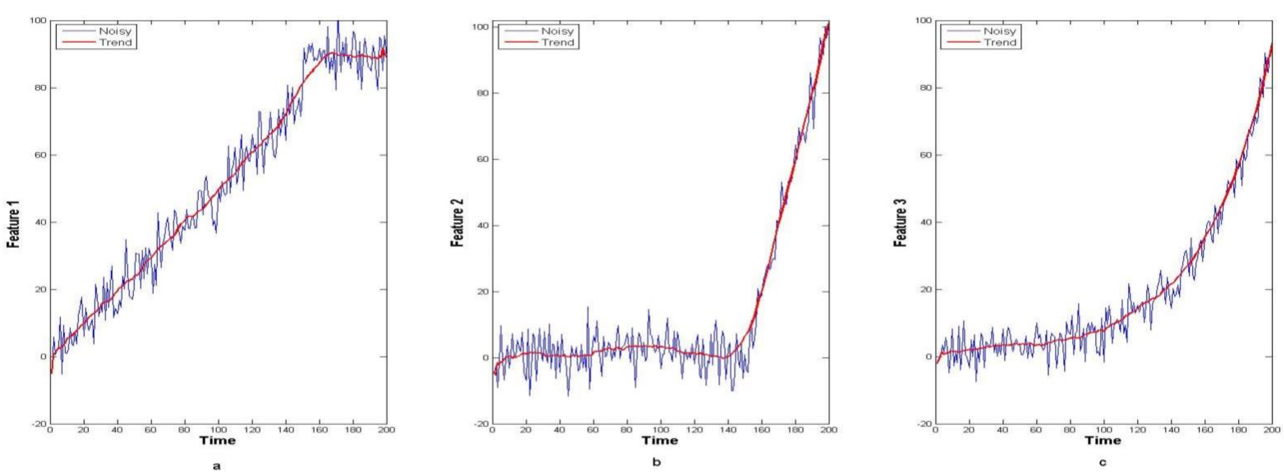

Figure 1. Features with different failure progression

method that aims to preserve the local and global structure has been presented in (Wang et al. 2014), and its application in prognostics has been discussed in (Peng et al. 2015).

Even though these feature evaluation studies on Prognostics has led to some level of success, they still miss an important aspect of the features and sensory data. The effectiveness of a feature or sensory data is not static throughout the life of the component or system under observation. A feature may be a good representative of the failure progression in the initial failure phase but not in the later part of the failure. In contrary a feature may be effective close to final phase of the failure but not in the initial phase. Thus, the single static evaluation of a feature for the full life of the system may not be effective. The bad failure progression representation in one part may negate the good failure progression representation in another part. This dynamic nature of the sensory information is handled with online PCA approaches for diagnostics and other classification problems as discussed above. This paper aims to fill this gap in prognostics by presenting a dynamic feature evaluation algorithm through identification of the good representative parts of features and using them in a dynamic equation throughout the life of the system.

3. METHODOLOGY

3.1. Problem Definition

Features react differently to the failure progression. Monotonically decreasing or increasing features with failure progression have been accepted as good representatives. However, the good representation may be partial in the life of the component or system. For example, three feature examples are given in Figure 1. The failure progression representation capability of feature 1 is very high in the first phase of the life as shown as continues increase. However, the feature stays constant with some noise towards the end of the component life (Figure 1.a). In contrary, the second feature does not represent the failure progression in the initial phase. It then becomes a good representative in the second part with increasing value (Fig 1.b). The third feature is a well representative of the failure progression in most of the component life (Figure 1.c).

Static analysis of these features may mislead the feature evaluation. It is important to take the most value from good representative phases of the features and avoid the effects of bad representative phases. A dynamic evaluation is expected to lead giving high importance in the first phase of the first feature and the second phase of the second feature and ignoring the remaining phases for both features. To the best of our knowledge, this problem has not been discussed in the literature yet. This paper aims to propose a feature evaluation and fusion algorithm for prognostics that can handle these types of features.

The problem defined above has two major steps: segmentation and fusion. Segmentation identifies the phases of the features that correlate with the failure progression differently. Fusion focuses on the integration process of the segmented features for effective prognostics. The process has been illustrated in Figure 2.

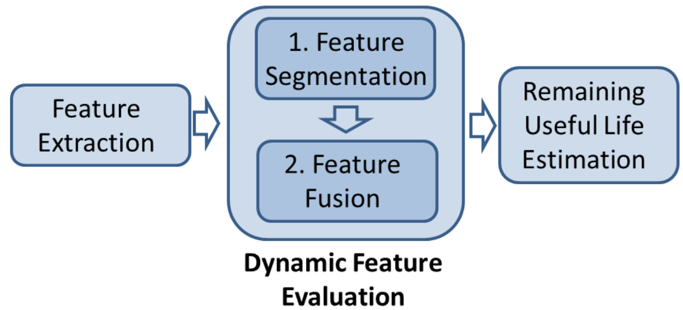

Figure 2. Steps of proposed approach

1. *Feature Segmentation:* Time series segmentation is a mature area and has been applied in many engineering fields. There are various approaches in time series segmentation such as Wavelets, Symbolic representations, Fourier transforms and Piecewise Linear Representation (Chan & Fu, 1999). Time series segmentation process can be defined as decomposition of time series data into homogenous segments or groups based on similar structure. In general time series analysis, segmentation is used for data reduction, trend analysis, pattern detection with similar behavior and for discretization. Time series segmentation algorithms can be categorized into three groups:
   A. Top-down: The segmentation starts from the whole time series data and continues recursively until predefined criteria is met. This is an offline method.
   B. Bottom-up: The segments in the time series are obtained by analysis of data points one by one. This is an offline method.
   C. Sliding Window: Data points within a window are analyzed to identify the segments and the window moves from beginning to the end of the time series data. This is an online method.

Readers are referred to (Koegh et al 2004) for more information about time series segmentation.

2. *Feature Fusion:* Feature fusion is the process of combining different features to enhance the SoH estimation of the electro-mechanical system. It is very difficult, if not impossible, to extract a single feature that perfectly represent the failure progression. Thus, it is important to extract value from different features for better SoH estimation. In this step, segmented features are fused via data fusion algorithm.

There are different methods used in the literature for fusion. Weighted average is one of the most widely used approach in fusion. Fusion is commonly used in diagnostics and prognostics. A novel fusion approach in RUL prediction based on superstatistic and information fusion has been presented in (Lui et al, 2014). Composite health index is obtained through fusion in (Lui et al, 2013) [26]. Neural network has been used in (Nui and Yang, 2010) for data fusion to achieve intelligent prognostics system.

3.2. Proposed Approach

The proposed approach has been discussed based on the steps discussed above.

Table 1. Sliding window pseudo code

```
sliding_window(Tdata,max_error):
anchor=1;
while not segmented Tdata
%w:window size
w=2;
iferr_calc(Tdata(anchor:anchor+w))<max_error
w=w+1;
else
%convert into segment
Tdata_segments<-Tdata(anchor:anchor+(w-1));
%update anchor with new point
   anchor=anchor+w;
end
end
```

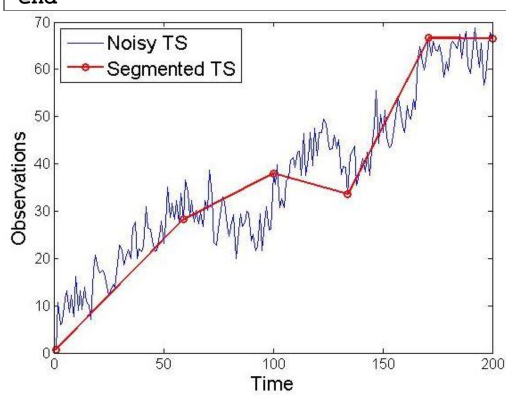

Figure 3. Segmented noisy time series

1. *Sliding Window Segmentation:*

Sliding window approach has been selected in this paper for segmentation of features for prognostics purposes due to its online property and good performance with noise. In sliding window segmentation algorithm the initial window includes the data points from the first to the n^{th} data points, where n is the length of the initial window (T {t_i: $i=1...n$}). A linear model has been fitted to the data points within the window. If the curve fitting error does not exceed a predefined threshold, the size of the window is increased to include the next data point outside of the window. This process continues until a point where the curve fitting error exceeds the threshold or end of the time series has been reached. When the curve fitting error exceeds the threshold, the last data point added to the window is defined as the start of the second segment. Table 1 gives the pseudo code of the segmentation algorithm and Figure 3 displays the output of the segmentation algorithm. Each line between dots represent a segment obtained by the model.

1. *Feature Fusion:*

Features may be in different scales. In order to use these features within the feature fusion process, they should be normalized. In order to achieve normalization, all features are converted in SoH values. The features are converted into SoH values based on the ratio of feature value at time $t(F_t)$ to the initial feature value. Equation (2) is the SoH calculation for the decreasing features with the failure progression, whereas equation (3) gives the SoH calculation for increasing features with the failure progression. Please note that maximum ($F_{max(1:T)}$) and minimum ($F_{min(1:T)}$) of first T values of the features are selected in order to handle potential noise within the features.

$$SoH_{i,t} = \frac{F_{i,t}}{\max(F_{i,1:T})}, \forall F_i \text{that decreases with failure progress} \quad (2)$$

$$SoH_{i,t} = \frac{\min(F_{i,1:T})}{F_{i,t}}, \forall F_i \text{that increases with failure progress} \quad (3)$$

The fusion process bases on weighted average calculation as shown in equation (4):

$$SoH_{f,t} = \frac{\sum_{i=1}^{N} w_i SoH_i}{\sum_{i=1}^{N} w_i} \quad (4)$$

The weight of each SoH estimation value obtained from a feature plays the crucial role in the fusion process. Initially, the feature weight values are set equal as shown in equation (5). In [24], the weight values are updated using the estimation error of features as shown in equation (6). This formula has been revised as in equation (7) to incorporate the representation capability of the failure progression. In other words, as the failure progresses, the weight values are updated based on the representation capability of the feature to the failure progression as well as the SoH estimation error for each feature.

$$w_i = {}^1\!/_n \qquad \forall i = 1, \dots n \quad (5)$$

$$w_{i,t+1} = \left(w_{i,t} + \left(1 - \left|SoH_{f,t} - SoH_{i,t}\right|\right)\right) \quad (6)$$

$$w_{i,t+1} = \left(w_{i,t} + \left(1 - \left|SoH_{f,t} - SoH_{i,t}\right|\right)\right) \times M_i \quad (7)$$

A feature's representation capability of failure progression has been quantified using monotonicity parameter (M_i). Monotonicity is calculated using continuously increasing or decreasing property of the feature as shown in equation (8). An ideal feature is expected to be either continuously increasing or decreasing. Increase in a feature is identified as the derivative being positive ($\# \frac{d}{dF} > 0$), whereas negative derivative ($\# \frac{d}{dF} < 0$) indicates decrease in consecutive feature values. The difference between number of positive and negative derivatives gives the monotonicity value. High value of the absolute value of this difference indicates high monotonicity. Highest possible monotonicity is one with having all derivatives (total on n-1 derivatives) being positive or negative. The lowest possible monotonicity is zero with having equal number of positive and negative derivatives.

Raw features F_i, $i=1 \ldots N$

↓

Segmentation process of F_i with $Sliding\_Window(F_i, max_{err})$ [Table1].

↓

For features with decreasing trend:

$$SoH_{i,t} = \frac{F_{i,t}}{\max(F_{i,1:T})} \quad (2)$$

For features with increasing trend:

$$SoH_{i,t} = \frac{\min(F_{i,1:T})}{F_{i,t}} \quad (3)$$

↓

Calculate the Monotonicity matrix:

$$M_i = \left| \frac{\# \frac{d}{dSoH_i} > 0}{n-1} - \frac{\# \frac{d}{dSoH_i} < 0}{n-1} \right| \quad (8)$$

↓

Weighted average fusion:

$$SoH_{f,t} = \frac{\sum_{i=1}^{N} w_i SoH_i}{\sum_{i=1}^{N} w_i} \quad (4)$$

Initialize weights:

$$w_i = {}^{1}/_{n} \qquad \forall i = 1, \ldots n \quad (5)$$

Weight update (7):

$$w_{i,t+1} = \left(w_{i,t} + \left(1 - \left|SoH_{f,t} - SoH_{i,t}\right|\right)\right) \times M_i$$

↓

Estimated $SoH_{f,t}$
by segment-based feature fusion

Figure 4: Estimation process of SoH through segment based fusion

$$M_i = \left| \frac{\# \frac{d}{dSoH_i} > 0}{n-1} - \frac{\# \frac{d}{dSoH_i} < 0}{n-1} \right| \quad (8)$$

The presented approach has been summarized in Figure 4. The next section presents the results of applying this methodology on simulated and real data.

4. RESULTS AND DISCUSSION

The presented approach has been implemented in two types of datasets: simulated data and Li-ion battery degradation data.

4.1 Simulation Results:

The simulation dataset has been obtained in two steps. A ground truth SoH value has been simulated first. Figure 5 displays the simulated SoH values. Then, six features have been simulated based on the SoH value. Each feature is created based on a function of SoH with some noise added. Two of the features (Feature 4 and 5) use a single function from beginning to the end of the failure progression. The other four features (Feature 1, 2, 3, and 6) have been divided into two segments. A distinct function has been used for each segment. In other words, more than one function have been used to obtain three features, each of which corresponds to a different phase of the failure progression. Figure 6 displays the selected simulated features.

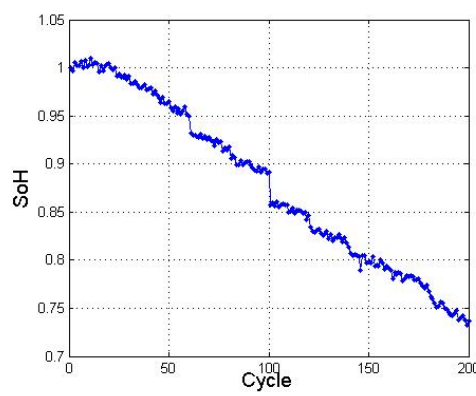

Figure 5. Ground truth SoH feature

In order to evaluate the value of the presented approach, SoH estimation has been performed under three scenarios. Scenario 1 involves utilizing all the features without segmenting them. Scenario 2 also involves unsegmented fusion, but using only selected features. Scenario 2 assures negative effect of any features in the SoH estimation, if any, by selecting the good features only. Scenario 3 involves the usage of the presented approach. All features have been segmented first and segmented features are utilized for fusion as discussed in the previous chapter.

The segmentation process has divided feature 1, 2, 3, and 6 into two parts. Feature 4 and 5 has not been divided since they have not exceeded the threshold. The segments obtained from these features have been displayed in Table 2.

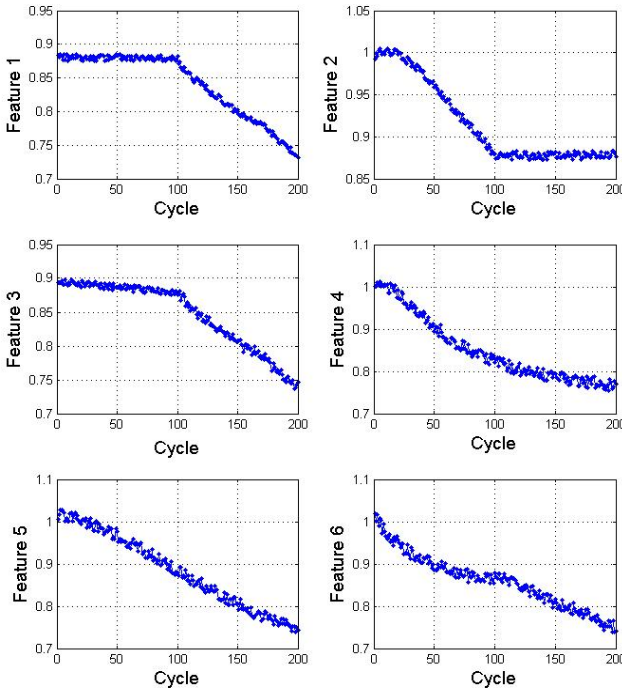

Figure 6. Simulated features

Table 2. Segmentation points for feature $\boldsymbol{F_i}$

$\boldsymbol{i}$	**1**	**2**	**3**	**4**	**5**	**6**
$F_i(1{:}S^1)$	103	99	110	x	x	98
$\boldsymbol{F_i(S^1+1{:}S^2)}$	200	200	200	x	x	200

S^1 stands for first segment point
x - features that segmentation led to one segment

The effect of the segmentation can be observed with the change of weight values used in the fusion. The change of weight values in the fusion process for all three scenarios for feature 1, feature 2 and feature 5 has been given in Figure 7. Feature 1, feature 2 represent segmented features, whereas feature 5 represent unsegmented features. As seen from the Figure 7.a, if features are not segmented, the weights of feature 1 and 2 are low due to the phase without a trend. Feature 5 has higher weight values since it has continues trend in the whole life.

As seen from the Figure 7.b, if the features are segmented, then first phase of the feature two has high weights due to the trend in the first phase. However, the weight values drop dramatically in the second phase. In contrary, the weight values of feature 1in the initial phase is low due to the lack of trend. They increase in the second phase with the trend. As a result, one can observe the value of segmentation through better evaluation of features in different phases of life with the changing weight values that are used in fusion process. Different phases contribute differently in the fusion process avoiding negative effect of a phase to the evaluation of a feature.

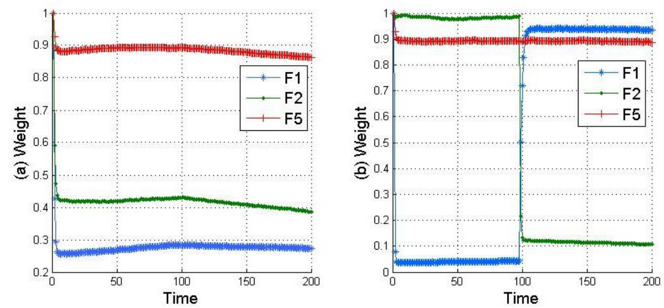

Figure 7. Weight changes in a) without segmentation, b) with segmentation

The change of weight values depends on the monotonicity of the features. High monotonicity leads to high weight values. Table 3 displays the monotonicity values for features in three scenarios. Monotonicity of all features without segmentation is given in the first column. If a feature is segmented, monotonicity values for each segment are given in last two columns. As seen from the table, segmentation process leads to two monotonicity values; one is lower, the other is higher than the monotonicity value of the same feature without segmentation. This shows that the negative effect of unsegmented approach when the same monotonicity is used for all phases of the feature. It is important to identify the phase that is highly correlated with the failure progression and give high importance to this feature in this phase as well as ignoring the uncorrelated phase.

Table 3. Feature monotonicity coefficients

		Unsegment	***Segmented***	
	$\boldsymbol{i}$	$\boldsymbol{F_i}$	$\boldsymbol{F_i(1{:}S^1)}$	$\boldsymbol{F_i(S^1+1{:}S^2)}$
Monotonicity coefficient	1	0.23	0,04	**0,42**
	2	0.16	**0,39**	0,07
	3	0.27	0,16	**0,38**
	4	0.43	x	x
	5	0.47	x	x
	6	0.41	0,35	**0,47**

Figure 8 displays the SoH estimation results for all three scenarios. As seen from the figure, the segmented fusion results give better SoH estimation. Especially improvement in SoH estimation in the first phase is better observed. SoH estimation errors for each feature individually and fused features are given in Table 4 as Root Mean Square Error (RMSE).As seen from the table, segmented fusion reduces the error more than half (from 0.032 or 0.025 to 0.012). Results show that segmentation based feature fusion improves SoH estimation.

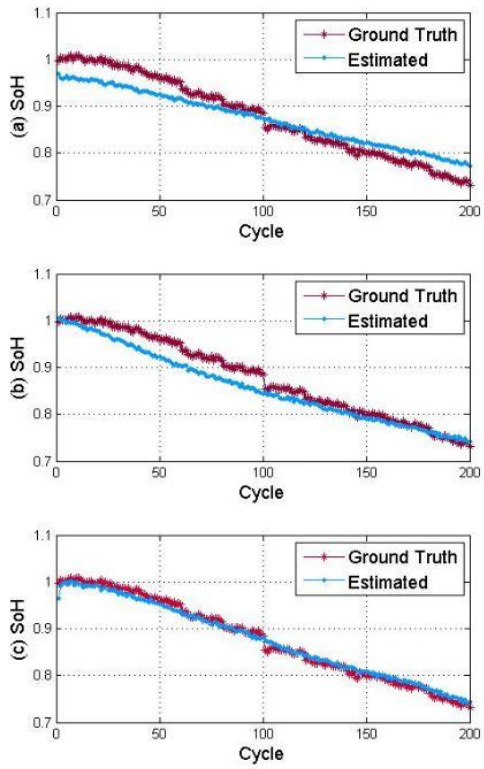

Figure 8. SoH estimation by fusion for a) Scenario 1, b) Scenario 2, c)Scenario 3

Table 4. SoH estimation errors

	F_1	F_2	F_3	F_4	F_5	F_6	Fused
Individual	0.059	0.060	0.054	0.039	0.015	0.036	
Unsegmented	✓	✓	✓	✓	✓	✓	**0.032**
Selected	×	×	×	✓	✓	×	**0.025**
Segmented	✓	✓	✓	✓*	✓*	✓	**0.012**

✓* - features that segmentation led to one segment, ✓ - features used, × - features not used

4.2. Li-ion Degradation:

Li-ion batteries have been used in many areas in today's world. SoH estimation and prognostics play crucial role in reliability, safety, and cost of lithium-ion batteries [28]. This section discusses application of the presented methodology on the degradation data obtained from li-ion batteries in the lab environment.

LiFePO4 14505 with 0.6Ah capacity and nominal voltage of 3.2V is used for tests. Figure 9 shows the experimental setup used for the accelerated degradation tests. An accelerated test consists of three main phases: cycling, test measurement, and characterization. Prior to cycling process, cell is kept under 45 ℃ for two hours to stabilize cell temperature. Cycling process for Li-ion cell is carried out by charging cell up to 3.6V with constant current of 0.6Ah which is known as galvonastatic mode and discharging cell up to cut-off voltage 2V, which is known as potentiostatic mode, with the same amount of current. After completing each 20 cycles, SoH and internal resistance features were tested to make sure whether aging threshold is met or not. A final characterization test takes place right after if the cell has met its predefined SoH threshold, where EIS and other characterization tests were applied to extract SoH indicatory features of cell. Figure 10 displays the procedure applied for the accelerated tests.

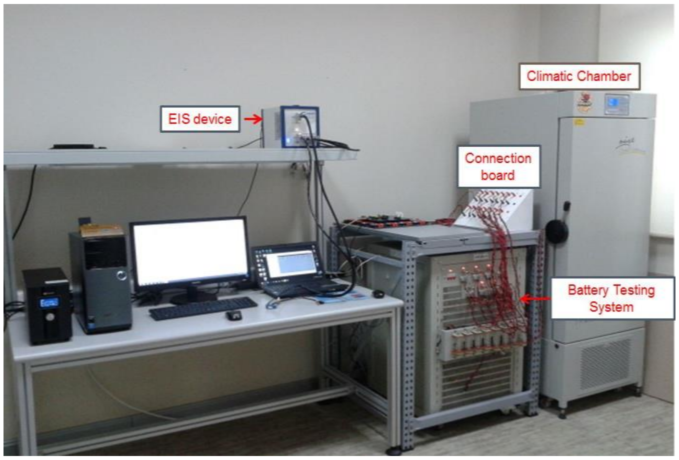

Figure 9. Experimental rig

Several measurements have been collected during the accelerated tests such as charge time, constant charge/voltage time, peak to peak values from charge/discharge rest time OCV curves (Figure 11), and internal resistances through Electrochemical Impedance Spectroscopy (EIS). These measurements have been further processed to obtain different features such as different types of resistances within the battery. Figure 12 displays the examples of the features through the life time of batteries.y-axis displays values of the features, whereas the x-axis gives the time within a cycle. The progression of the features as the battery degrades is shown as different lines in the figure. The change in the shape of the line in the figure indicates the failure progression.
Capacity shown as first graph in the figure above is discharge capacity obtained through integration of discharge current using Coulomb Counting. Capacity is used as the ground truth SoH value to be used for comparison of SoH estimations. Following features for Li-ion battery degradation have been used for SoH estimations: Feature 1 charge time (Chg) time spent in both galvonastatic and potentiostatic modes of charging process. Feature 2 is constant current charge time (CC) spent for battery to reach voltage level of 3.6V. Feature 3 is the time spent for charging with reducing current up to 60 mAh after voltage reaches to 3.6V. Feature 4 is calculated from individual charge OCV curves as the distance between peak values. Similarly feature 5 is obtained from individual discharge OCV curves. Features 6, 7, 8, and 9 are internal resistances at 100 and 0% SoC levels

measured through electrochemical impedance spectroscopy (EIS).

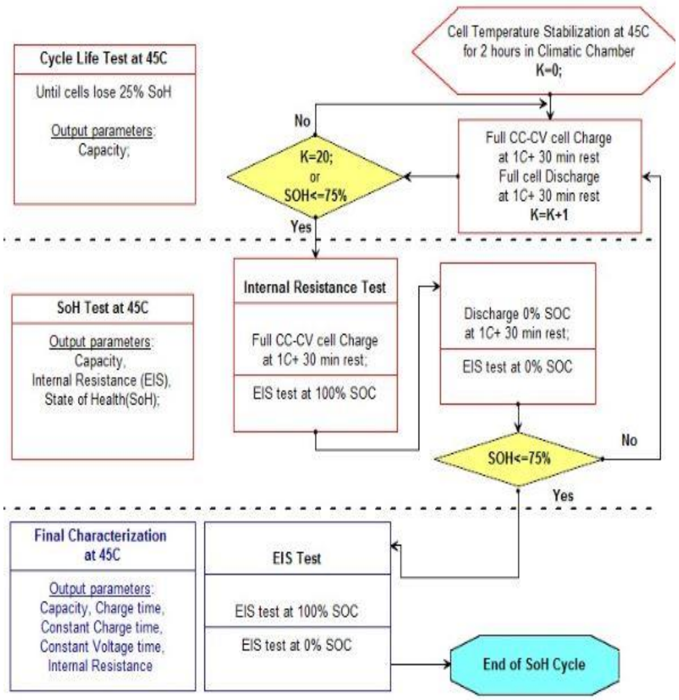

Figure 10. Diagram of aging cycle and characterization steps

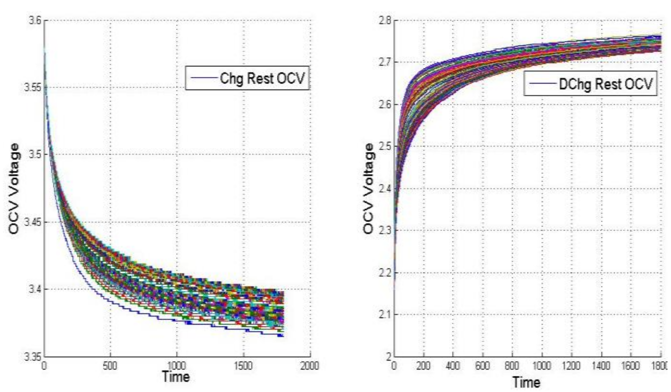

Figure 11. Charge/Discharge OCV curves at resting time.

The features have been converted into SoH values using the formulas in equation (2) and (3).The SoH obtained from the individual features are depicted in Figure 13.

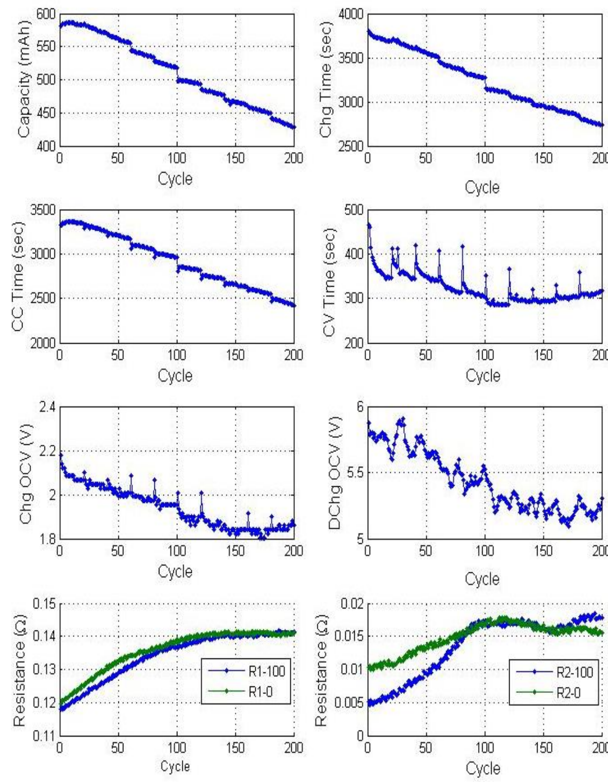

Figure 12. Features obtained with degradation of Li-ion battery

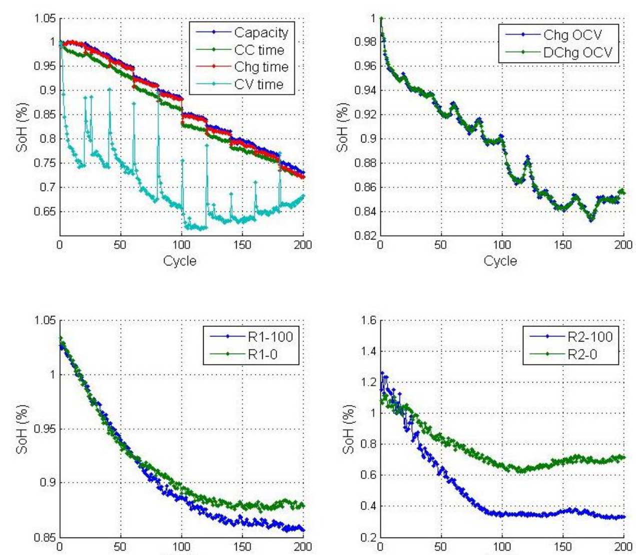

Figure 13. SoH change based on individual features.

Since Li-ion batteries are electro-chemical substances, degradation of batteries are highly dependent onto the environmental changes such as; temperature and aging cycle profiles. Thus, accurate SoH estimation of Li-ion batteries should involve analysis of multiple features. The fusion process has been performed using two scenarios to evaluate the value of the presented approach. Scenario 1 involves fusion of all features without segmentation process, whereas Scenario 2 involves fusion of all features with segmentation.

The weight values of three features (i.e., charge time, resistance R1 and R2) used in the fusion process for both scenarios are displayed in Figure 14. As seen in Figure 14.a, weight values are stable since no segmentation is involved. When segmentation is applied, the weight values of features 'R1 and R2' decreases in the second phase (after 107th cycle for R1, 105th for R2). This can easily be understood by observing the change in the trend in the initial and latter phases of the features. The drop in weight values of R1 is higher since the trend difference between the phases is higher.

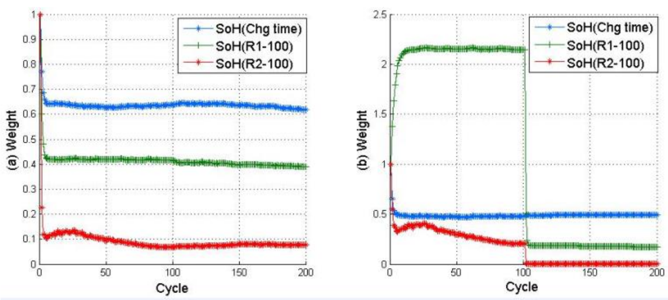

Figure 14. Weight change a) without segmentation, b) with segmentation only for R1 and R2.

Table 5 displays the monotonicity values used to obtain the weight for the features in two scenarios. Monotonicity values of unsegmented features as well as phases of features for segmented features are given in the table. As seen from the table, the monotonicity values are increased when the features are segmented compared to the monotonicity values without segmentation.

Table 5. Feature monotonicity coefficients

		Unsegment	*Segmented*	
	i	F_i	$F_i(1\!:\!S^1)$	$F_i(S^1+1\!:\!S^2)$
Monotonicity coefficient	1	0.86	x	x
	2	0.73	x	x
	3	0.22	**0.50**	0.07
	4	0.28	**0.45**	0.08
	5	0.38	**0.56**	0.16
	6	0.44	**0.68**	0.16
	7	0.34	**0.57**	0.02
	8	0.17	**0.29**	0.01
	9	0.16	0.14	**0.18**

Figure 15 displays the SoH estimation results for both scenarios. As seen from the figure, the segmented fusion results give better SoH estimation. The SoH estimation errors based on individual features and fused features with and without segmentation are given in Table 6 as Root Mean Square Error (RMSE). As seen from the table, the estimation error has been reduced more than half in the segmented analysis compared to the unsegmented analysis.

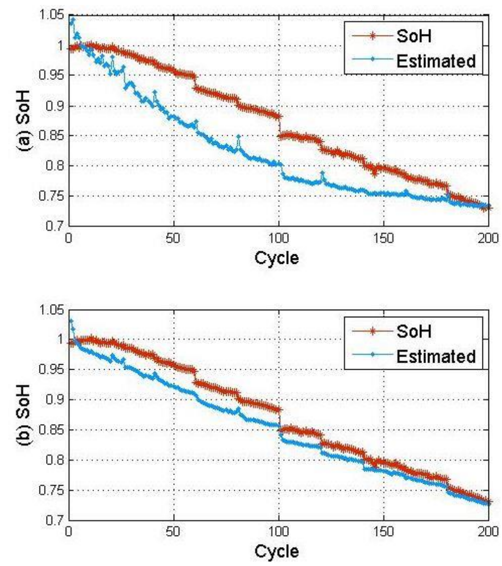

Figure 15. SoH estimation by fusion for a) Scenario 1, b) Scenario 2.

Table 6. SoH estimation errors

	F_1	F_2	F_3	F_4	F_5	F_6	Fused
Individual	0.059	0.060	0.054	0.039	0.015	0.036	
Unsegmented	✓	✓	✓	✓	✓	✓	**0.032**
Selected	×	×	×	✓	✓	×	**0.025**
Segmented	✓	✓	✓	✓*	✓*	✓	**0.012**

✓* - features that segmentation led to one segment, ✓ - features used, × - features not used

As depicted in Figure 16 above, integrating all features without segmentation does not make fusion to converge to the SoH efficiently. Feature fusion with dynamic feature evaluation through segmentation gives pretty good results in SoH estimation.

5. CONCLUSION

Static analysis of features based on the whole life cycle may mislead the feature evaluation. Features may reflect the SoH differently in different phases of the life of the electro-mechanical system. It is important to take the most value from good representative phases of the features and avoid the negative effects of bad representative phases. A methodology for dynamic evaluation of features has been presented. A fusion process has been developed that use the dynamic evaluation of features that involves segmentation of features based on monotonicity. The presented approach has been demonstrated in simulated and Li-ion battery degradation data. The results show that segmentation of features prior to fusion improves SoH estimation results. Optimization of number of segments and handling variance in segmentation points from different samples are the future research topics.

ACKNOWLEDGEMENT

This research was supported by The Scientific and Technological Research Council of Turkey (TUBITAK) under project number113M093.

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