

Trend Regeneration of Health Parameter in a Developmental Aero Gas Turbine Engine

Usha Srinivasan, K. R. Sudhindra, N. Muthuveerappan



Abstract: Health parameters play a vital role in determining the remaining useful life of engine components, ensuring safe and confident continual test trials during the development phase. Although enough care is taken to obtain the health parameter data throughout the engine test duration, there are chances of missing out a few for reasons beyond control. This paper aims at providing a feasible solution to mitigate the data loss by regenerating the health parameter trend. Least square approximation, data mapping with threshold and interpolation techniques have been attempted via software development for trend regeneration. Two tier data fusion software has been developed to gather the data required for trend regeneration. Considering strain for case study, using actual test trial data, software has been verified. Interpolation technique with the least error emerged as an optimal choice and ensuring acceptance of its estimated strain trend resulted in its confident usage enabling intended progressive research.

Keywords: Interpolation, Least Square Method, Remaining Useful Life, Root Mean Square Error, Sensor Data Fusion

I. INTRODUCTION

A developmental engine is monitored by the evaluation of component health with respect to the correctness of its design intent by using the data acquired from multiple sensors via multiple systems. While the performance parameters like pressures and temperatures track slower changes in engine condition, health parameters like vibration and strain serve as indicators of sudden changes in the state of the engine [1]. The time left before noticing a failure called the residual life or remaining useful life is estimated based on the machine condition and its operating profile [2],[3]. RMS error serves as metric for Remaining Useful Life (RUL) prediction [4]. An engineering approach to reliability is based on the actual change in unit health which determines the current condition of an operating unit [5]. Multi-sensor information fusion is used to realize the RUL prediction and the RUL prediction model is based on polynomial curve fitting method [6]. Health parameters being the key source indicating the engine condition, its non-availability becomes a bottleneck during the developmental phase.

Further in cases where the health parameter data is missed out, there is a mandatory requirement to regenerate at least the trend of the health parameter to detect the changes in the engine state prior to any event to safeguard the engine under test. Towards this objective, various regeneration methodologies were tried out aimed at enabling detection of missing health parameter data followed by its trend prediction. As a pre-requisite to the estimation of the health parameter trend, there was a requirement to collect the desired sensor data acquired in multiple systems. The concept of assimilating better quality information using a combination of multiple sources is termed as data fusion [7]. Data fusion simply amounts to the integration of data and knowledge obtained from several sources. With a wealth of potential data that can be acquired from any unit under test the level of data fusion is decided based on the specific application [8]. The main levels of data fusion include:

- Sensor level fusion:** Combines multiple sensors measuring correlated parameters. Safety being the primary concern in an aircraft engine, its health needs to be continually monitored to know the status of the engine components in terms of faults or degradations to enable the prediction of its Remaining useful life [9].
- Feature level fusion:** The analyzed results from multiple analysis methods are combined.
- Decision level fusion:** Diagnostic actions to include damage assessment and maintenance advisories are combined

The herculean task of, detecting missing data and carrying out the data fusion of selected parameters using voluminous test trial data called for a two tier data fusion software development.

Having accumulated the desired sensor data based on which it was intended to estimate the health parameter trend, various methodologies were explored for regenerating the health parameter trend. Curve Fitting is a technique to model the data by creating a function [10]. Curve Fitting is a predictive analysis process which aims to generate a curve depicting a mathematical function to give a best fit for the desired data points [11].

Though the curve does not exactly fit the desired data points, it provides an approximate fit wherein the estimated trend is as close as possible to the actual trend. Least Square approximation is the commonly used method to fit a curve to an experimental data [12]. In the curve fitting problem, two conflicting aspects namely simplicity and goodness-of-fit are desirable [13]. Goodness of fit statistics indicates that a methodology with low RMS error is the candidate of choice [14].

Revised Manuscript Received on January 30, 2020.

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Implementation of different curve fitting methodologies in software enables easy computation of the RMS error between the measured and the curve fitted data [15]. To obtain a straight line of the best fit, for a set of two dimensional points, the sum of the absolute values of the vertical deviations of the points from the line should be minimum[16].

The Least Squares method is the most widely used curve fitting techniques due to its mathematical and computational simplicity leading to the ease of implementation [17]. Although there are different types of interpolation methods, the optimal choice depends on the application [18]. The nearest neighbor method is useful for filling a few missing values in the data. The basic Shewhart mean chart which monitors the mean of a process comprises of a center line along with Upper Control Limit (UCL) and Lower Control Limit (LCL) set at $\pm 3\sigma$ from the center line [19]. The estimation process for filling the data holes needs to be evaluated using the estimated control limits derived with the mean and standard deviations of the measured data. If the estimation C_1 is such that $LCL < C_1 < UCL$ for all the 'I' data points, then the estimation process is declared to be in control [20]. On the other hand even if one estimated data point falls on or outside the control limits, the estimation process is said to out-of-control. Normalization is a pre-processing step which removes dependence upon absolute amplitudes, whilst preserving information about the general shape of signatures[21]. Unit normalization preserves the shapes of patterns by scaling such that all amplitudes vary within the same range, between Zero and One.

II. REQUIREMENT FOR MULTI SENSOR DATA FUSION

In any developmental engine, the trend of the health parameters serve as ready reckoner to watch out the component's degradation, providing critical information on its Remaining Useful Life (RUL). RUL is a valuable input to enable crucial managerial decisions pertaining to the continual usage of the components in the subsequent test trials without compromising on the safety aspects. This is the normal strategy adopted when health parameter measurements acquired by sensors are readily available throughout the test trials. The major problem is encountered when the health monitoring parameters are not available due to reasons like discontinuity in lead wires, unexpected high environmental temperatures, health parameters values being exceptionally high beyond the design intent, etc...Under these circumstances, lack of information on RUL of the components inhibits confident continual of the test trials. The feasible solution to address this issue is to regenerate the trend of the health parameter, using the data from the corresponding associated aerodynamic parameters. In order to establish a feasible relationship between the aerodynamic performance parameters and the health parameters there is a requirement to collect the data acquired from multiple sensors via multiple systems. Thus multi-sensor data fusion becomes a pre requisite for estimation of the health parameter trend.

III. IMPLEMENTATION STRATEGY FOR MULTI-SENSOR DATA FUSION

Data from multiple sensors identified by specific parameter names are being acquired by different systems having various bandwidths. The availability of the data in each of the acquisition system as identified by the parameter names along with the bandwidth is given as inputs to data fusion software. A component wise listing of the aerodynamic parameters required for estimating the health parameter of that component is also made available to the software based on the component designer's inputs. Using these inputs data from multiple systems associated with a desired component are extracted at two levels based on the bandwidths of the systems. On one hand, the engine speed and multiple aerodynamic performance parameters are acquired and stored at a specific bandwidth. On the other hand the engine speed and the health parameters are acquired and stored at a bandwidth much higher than that used for acquiring the aerodynamic performance parameters. Using a common parameter namely the engine speed which is available at both the bandwidths, the data from both the performance parameters and the health parameters needs to be pooled using data fusion techniques.

The huge raw data pertaining to the aerodynamic performance parameters, acquired and stored during the test trials is made available to the users across multiple files in the form of engineering units for analysis. From these files a search is made to obtain the desired aerodynamic performance parameters based on the parameters specified by the designer with respect to the specific component. Since the data in these files are available at a common bandwidth, they can be easily merged together in a reference file. However to integrate the health parameter data to the reference file, there is a need to bring the health parameter data which is available at a higher bandwidth, to the common bandwidth before data fusion. Thus two levels of data fusion is envisaged for each test trial, to generate the basic reference files using the respective engine test trial data.

The first level of data fusion, aims to search and collect the designer specified parameter values from multiple input files and tabulate the same in a single file for various speed measurements ranging from 0% to 100% in steps of 0.1%. To accomplish this, software module has been developed which takes the designer specified parameters as inputs to generate an output table of $M \times N$. Here the N th column corresponds to the health parameter measurement and is left blank to be updated in the second level of data fusion. The M rows of the table correspond to the speed measurements ranging from 0% to 100% in steps of 0.1%. The $N-1$ columns correspond to the data values of the designer specified performance parameters which are being obtained by searching from multiple files and tabulated for each value of the speed. At the second level, the health parameter data available at a higher bandwidth is averaged and made available at the desired lower bandwidth in order to make it suitable to be merged along with the table generated in the first level of data fusion.

Thus the output of the second level of data fusion is a table comprising of the performance parameters and the health parameter for various speed measurements. The table thus generated may or may not contain the health parameter data based on its availability or non-availability respectively. Tables which contain the health parameter values serve as reference tables which are used to derive the health parameter values in tables where the health parameter data is missing.

Thus two levels of data fusion are being carried out by the software developed in LabVIEW for each test trial data to generate either a reference file or a missing data file depending on the presence or absence of the health parameter data. In the case of missing data file, the unavailable data is obtained from the trend regeneration methodology and updated at the respective locations in the N^{th} column.

IV. TREND REGENERATION METHODOLOGIES

In order to regenerate the health parameter trend, the following three strategies have been deployed namely:

- i. Least Squares Approximation
- ii. Data Mapping with Threshold
- iii. Interpolation

In each method which is being tried out under the above strategies, the Root Mean Square (RMS) error which quantifies the "closeness of fit" specifies the "error in the fit". Our objective is to try out various methods and try to reduce the RMS error to the minimum possible value. To enable trend regeneration, software has been developed in LabVIEW.

To verify the trend regeneration software, the engine component under consideration is the compressor stator vane and the health parameter which is considered for the trend regeneration is the strain. To accomplish this, the strain data in one of the test trial output is masked to serve as a missing data file. It has also been ensured that the reference data file for this selected test trial is not included in the set of reference files used for trend regeneration. The trend regeneration software incorporating various approaches enabling estimation of missing data for the selected case study is explained in the following sub-sections.

A. Least squares approximation

Considering the two conflicting desirable requirements of Curve fitting namely simplicity and goodness of fit, the work has been initiated with a simple linear fit and gradually moving onto the polynomial fit. Using Least Squares approximation, four different methods have been tried out to regenerate the strain data trend namely:

- i. UnivariateLeast Square Linear (ULSL)
- ii. UnivariateLeast Square Quadratic (ULSQ)
- iii. BivariateLeast Square Linear (BLSL)
- iv. BivariateLeast Square Quadratic (BLSQ)

1. UnivariateLeast Square Linear:

An attempt was made to deduce the strain value as a function of the pressure ratio using (1).

$$y = mx + c \quad (1)$$

Here y represents the strain value, x is the pressure ratio, m indicates the slope and c is a constant.

The slope and the constant of the linear equation are derived from the pressure ratio and the strain values contained in the reference files. Using values of m and c , the missing strain data was computed as a function of the corresponding pressure ratio and updated in the missing data file. The trends of estimated strain data along with the measured strain data at various engine speeds is depicted in Fig. 1 in normalized form. The corresponding measured and the estimated strain data values along with the RMS error are listed in Table I.

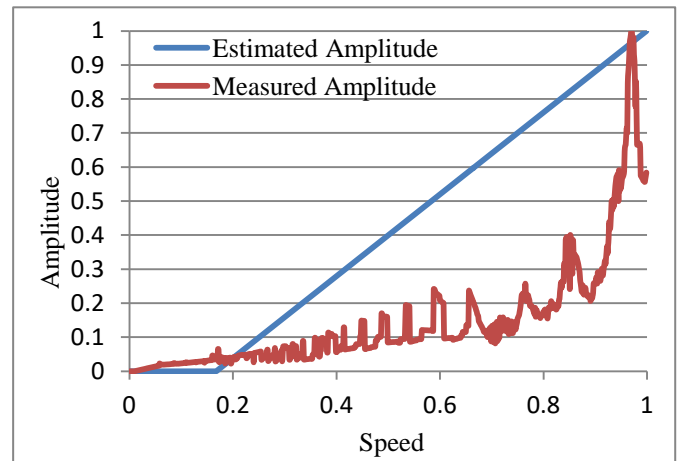


Fig. 1. Strain Vs Speed using ULSL

Table-I : ULSL Data

Estimated Amplitude	Measured Amplitude	Error
0.159301	0.0735988	0.085702
0.160503	0.0737008	0.086802
0.161706	0.0738027	0.087903
0.162909	0.0681219	0.094787
0.164112	0.0682389	0.095873
0.165314	0.0683559	0.096958
0.166517	0.0684729	0.098044
0.16772	0.0685899	0.09913
0.168922	0.0687069	0.100215
0.170125	0.0340369	0.136088

RMS Error = 0.35

2. Univariate Least square quadratic:

An attempt was made to deduce the strain value as a function of the pressure ratio using (2)

$$y = ax^2 + bx + c \quad (2)$$

Here y represents the strain value, x is the pressure ratio, a , b and c are constants.

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The constants of the quadratic equation were programmatically obtained from the pressure ratio and the strain values contained in the reference files. Using the constant values of a, b and c, the missing strain data was computed as a function of the corresponding pressure ratio and updated in the missing data file. The trends of estimated strain data along with measured strain data at various engine speeds is depicted in Fig. 2 in the normalized form.

The corresponding measured and the estimated strain data values along with the RMS error are listed in Table II.

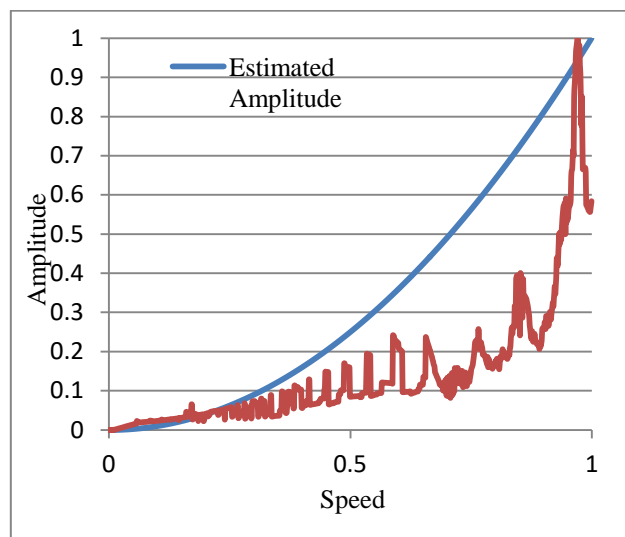


Fig. 2. Strain Vs Speed using ULSQ

Table-II : ULSQ Data

Estimated Amplitude	Measured Amplitude	Error
0.090053	0.0735988	0.016454
0.0906549	0.0737008	0.016954
0.0912589	0.0738027	0.017456
0.0918649	0.0681219	0.023743
0.0924729	0.0682389	0.024234
0.0930828	0.0683559	0.024727
0.0936948	0.0684729	0.025222
0.0943088	0.0685899	0.025719
0.0949248	0.0687069	0.026218
0.0955428	0.0340369	0.061506

RMS Error = 0.27

3. Bivariate least square linear:

An attempt was made to deduce the strain values as a function of engine speed and pressure ratio using (3)

$$y = ax_1 + bx_2 + cx_1x_2$$

(3)

Here y represents the strain value, x_1 the engine speed, x_2 the pressure ratio, while a, b and c are constants.

The constants of the linear equation were programmatically obtained using two variables namely the Engine Speed and pressure ratio for the strain values contained in the reference files. Using the constant values of a, b and c, the missing strain data was computed as a function of the

corresponding engine speed and pressure ratio and the same was updated in the missing data file. The trends of estimated strain data along with measured strain data at various engine speeds is depicted in Fig. 3 in the normalized form. The corresponding measured and the estimated strain data values along with the RMS error are listed in Table III.

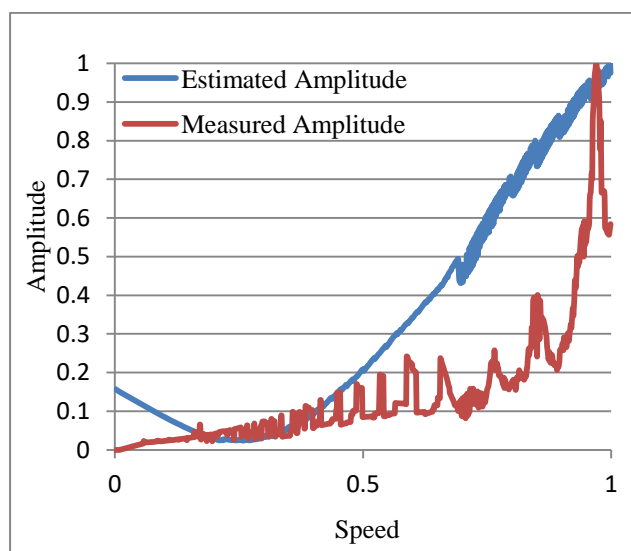


Fig. 3. Strain Vs Speed using BLSL

Table-III : BLSL Data

Estimated Amplitude	Measured Amplitude	Error
0.034268	0.0735988	0.039331
0.035374	0.0737008	0.038327
0.0364808	0.0738027	0.037322
0.0331663	0.0681219	0.034956
0.0343041	0.0682389	0.033935
0.0354425	0.0683559	0.032913
0.0365815	0.0684729	0.031891
0.0377211	0.0685899	0.030869
0.0388613	0.0687069	0.029846
0.0375706	0.0340369	0.003534

RMS Error = 0.26

4. Bivariate least square quadratic:

An attempt was made to deduce the strain values as a function of engine speed and pressure ratio using (4)

$$y = ax_1 + bx_2 + cx_1x_2 + d x_1^2 + ex_2^2$$

(4)

Here y represents the strain value, x_1 the engine speed, x_2 the pressure ratio, while a, b, c, d and e are constants.

The constants of the quadratic equation were programmatically obtained using two variables namely the engine speed and pressure ratio for the strain values contained in the reference files. Using the constant values of a, b, c, d and e, the missing strain data was computed as a function of the corresponding engine speed and pressure ratio and the same was updated in the missing data file.

The trends of estimated strain data along with measured strain data at various engine speeds is depicted in Fig. 4 in normalized form. The corresponding measured and the estimated strain data values along with the RMS error are listed in the Table IV.

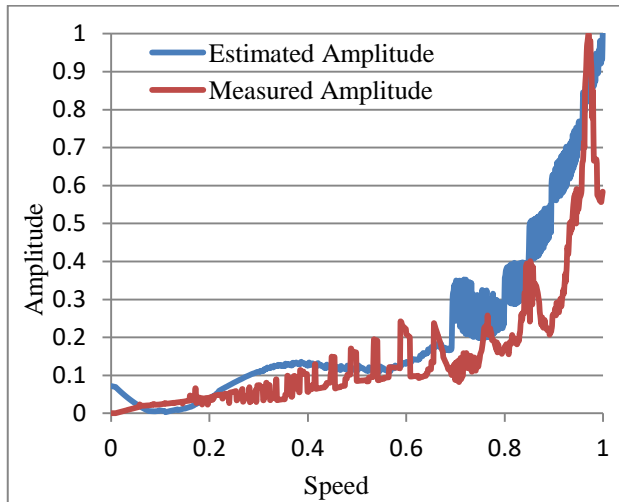


Fig. 4. Strain Vs Speed using BLSQ

Table-IV : BLSQ Data

Estimated Amplitude	Measured Amplitude	Error
0.109084	0.0735988	0.035485
0.108962	0.0737008	0.035261
0.108811	0.0738027	0.035008
0.111945	0.0681219	0.043823
0.111816	0.0682389	0.043577
0.111659	0.0683559	0.043303
0.111474	0.0684729	0.043001
0.111262	0.0685899	0.042672
0.111023	0.0687069	0.042316
0.112793	0.0340369	0.078756

RMS Error = 0.12

B. Data mapping using threshold

An attempt was made to search the reference files for specific combinations of speed and its corresponding pressure ratio from 0% to 100% speed in steps of 0.1% speed, to check the availability of the appropriate strain value. In cases where the strain data was readily available, the same was updated in the Nth column of the missing data file. In cases where the strain values were not readily available, keeping a set threshold for the pressure ratio, a search was made to obtain the strain value within the threshold limit. The value of strain data thus obtained was updated in the Nth column of the M x N table generated in the process of data fusion. Data Mapping has been attempted using various threshold limits and two of them have been depicted. The trends of estimated strain data along with measured strain data at various engine speeds with threshold of 0.1 and 0.001 is depicted in Fig. 5 and Fig. 6 respectively. The corresponding measured and the

estimated strain data values along with the RMS error are listed in the Table V and Table VI respectively.

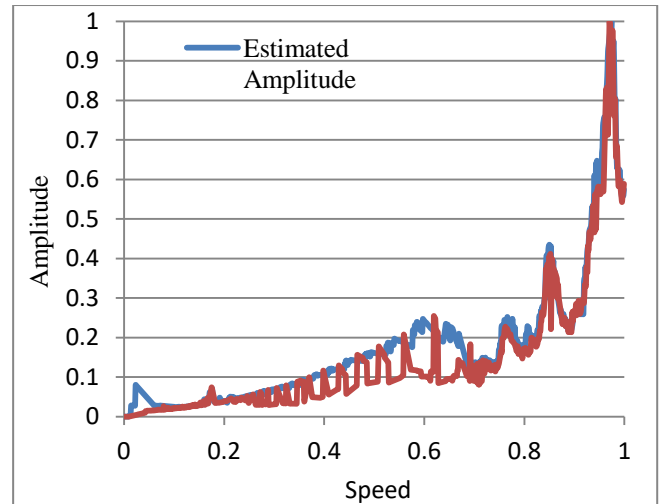


Fig. 5. Strain Vs Speed using threshold of 0.1

Table-V : Data for threshold of 0.1

Estimated Amplitude	Measured Amplitude	Error
0.1117486	0.0735988	0.0381498
0.1118042	0.0737008	0.0381034
0.1118595	0.0738027	0.0380568
0.1024787	0.0681219	0.0343568
0.1027349	0.0682389	0.034496
0.0744866	0.0683559	0.0061307
0.0710673	0.0684729	0.0025944
0.0695318	0.0685899	0.0009419
0.0731852	0.0687069	0.0044783
0.0420515	0.0340369	0.0080146

RMS Error = 0.05685

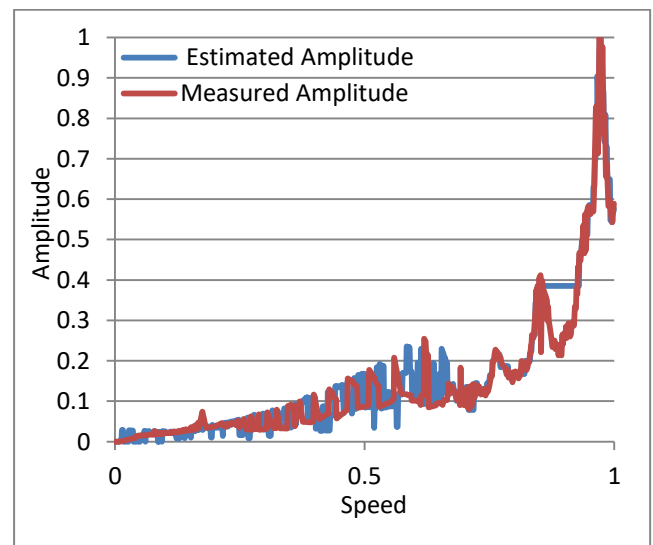


Fig. 6. Strain Vs Speed using threshold of 0.001

Table-VI : Data for threshold of 0.001

Estimated Amplitude	Measured Amplitude	Error
0.0378618	0.0735988	0.035737
0.0377808	0.0737008	0.03592
0.0380257	0.0738027	0.035777
0.0670019	0.0681219	0.00112
0.0338639	0.0682389	0.034375
0.0267089	0.0683559	0.041647
0.0303419	0.0684729	0.038131
0.0339759	0.0685899	0.034614
0.0204889	0.0687069	0.048218
0.0153299	0.0340369	0.018707

RMS Error = 0.04507

Table-VII : Interpolation Data

Estimated Amplitude	Measured Amplitude	Error
0.0560068	0.0735988	0.017592
0.0562508	0.0737008	0.01745
0.0564957	0.0738027	0.017307
0.0509569	0.0681219	0.017165
0.0512509	0.0682389	0.016988
0.0444019	0.0683559	0.023954
0.0534699	0.0684729	0.015003
0.0568069	0.0685899	0.011783
0.0601449	0.0687069	0.008562
0.0286959	0.0340369	0.005341

RMS Error = 0.04

C. Interpolation

In this methodology for each specific value of the engine speed and its corresponding pressure ratio, a search was made in the reference files to obtain the value of the associated strain. The process is straight forward in cases where the mapping was possible. In cases where the exact match could not be traced, the strain data was generated through piecewise linear interpolation. From the reference data files, two values of pressure ratios were traced, one above and one below the specific engine speed. For each of these pressure ratios the corresponding strain values were obtained from reference files and using these two strain values, the strain at the intended pressure ratio was obtained using interpolation and updated in the missing data file. For pressure ratios at the extremes, appropriate logic has been implemented to obtain the strain values. The trends of estimated strain data along with measured strain data at various engine speeds is depicted in Fig. 7 in normalized form. The corresponding measured and the estimated strain data values form along with the RMS error are listed in the Table VII.

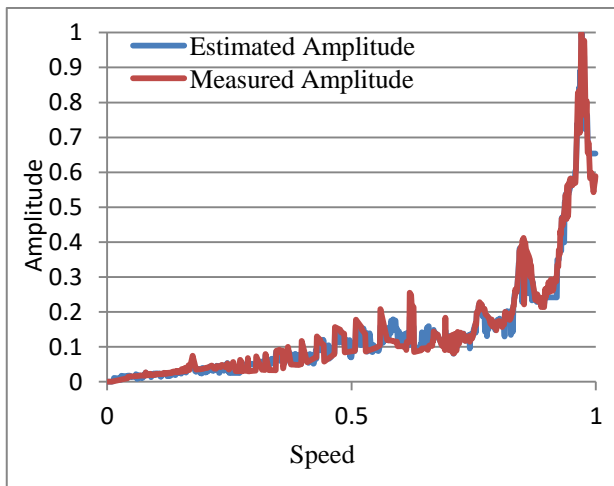


Fig. 7. Strain Vs Speed using interpolation

V. ACCEPTANCE OF ESTIMATION FOR IMPLEMENTATION

Having arrived at a minimum value of an RMS error of 4% using interpolation technique, an attempt has been made to check the acceptance of this estimated strain using the mean and standard deviation corresponding to the measured strain. The standard deviation also called as sigma(σ) is a metric used by analysts and statisticians to measure the variations from the mean. Three sigma limits which refers to the data within three standard deviations from the mean, is used in statistical quality control to set the upper and lower control limits. The UCL is set to $(\mu + 3\sigma)$ and LCL is set to $(\mu - 3\sigma)$. If the data points lie within UCL and LCL then, they are said to be within statistical control. Using a set of ten test trial data where the strain values are available from the measurement, the mean (μ) and Standard Deviation (σ) has been computed. Using these values the allowable limits with respect to the mean has been arrived corresponding to $\mu \pm 3\sigma$. The boundary corresponding to $\mu \pm 3\sigma$ on either side of the mean defines the envelop of the permissible strain. The estimated response obtained by interpolation method, using a test trial data with the strain values masked is depicted in Fig. 8. The ten test trials used for computing mean and standard deviation does not include the test trial which is being used for obtaining the estimated response. The fact that the estimated response is well within the permissible boundaries of LCL and UCL clearly indicates that the estimation process is "In-control".

Following plots are depicted in Fig. 8 :

- i. Mean value of the measured strain Vs speed
- ii. $\mu + 3\sigma$ of the measured strain Vs speed
- iii. $\mu - 3\sigma$ of the measured strain Vs speed
- iv. Estimated strain Vs speed (estimation is by interpolation method)

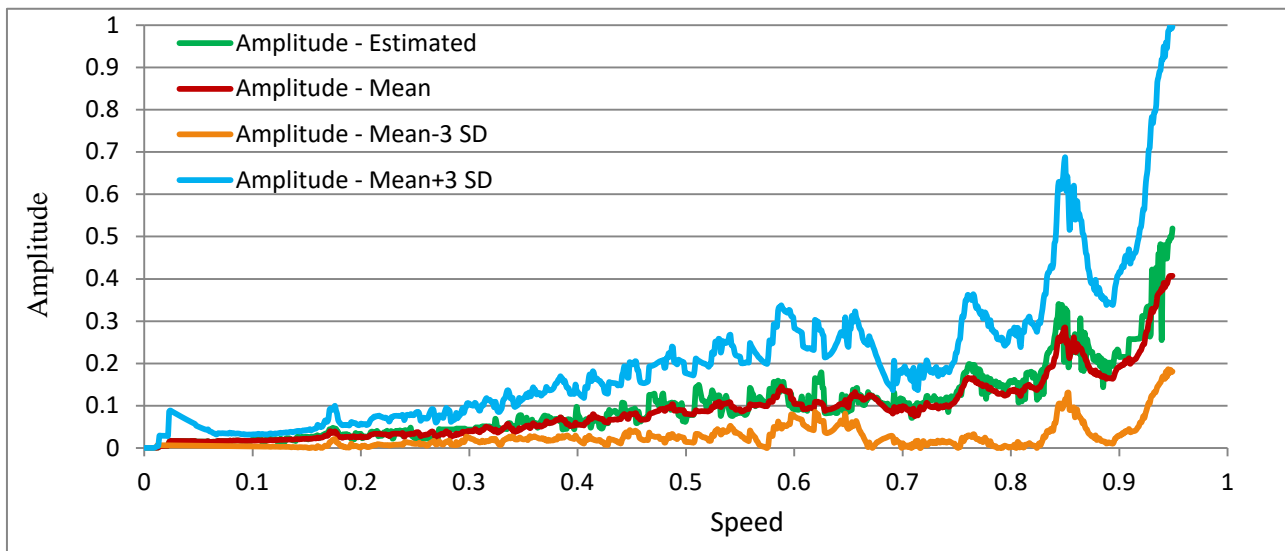


Fig. 8. Combined plot of measured μ , $\mu+3\sigma$ and $\mu- 3\sigma$ along with estimated strain Vs speed

VI. RESULTS AND DISCUSSION

Stress of a component being an estimator of RUL, its measurement is a pre-requisite for continuing further test trials. Since stress is computed by measuring the strain data, its availability becomes a mandatory requirement for ensuring safe test trials. When the strain measurement is not available in test trial data, its trend needs to be regenerated by using other available parameters like speed, pressure, temperature etc. An attempt was made to establish a relationship between

the available parameters individually with strain trend. The study indicated the absence of a one-to-one relationship between strain and any other available parameter. To deduce a relationship between the other available parameters and strain, combination of the available parameters was considered. Since the pressure fluctuations predominantly affect the stress of any component, an attempt was made using the pressure ratio (a combination of inlet and exit pressures), to arrive at a relationship between strain and pressure ratio.

Table-VIII: Results

Sl.No	Strategy	Methodology	Parameters Deployed	RMS Error in Percentage
1	Least Square Approximation	ULSL	Pressure Ratio	35
		ULSQ	Pressure Ratio	27
		BLSL	i)Speed ii)Pressure Ratio	26
		BLSQ	i)Speed ii)Pressure Ratio	12
2	Data Mapping with Threshold	Threshold of 0.1 set for the pressure ratio	i)Speed ii)Pressure Ratio	5.6
		Threshold of 0.001 set for the pressure ratio	i)Speed ii)Pressure Ratio	4.5
3	Interpolation	Piecewise Linear Interpolation	i)Speed ii)Pressure Ratio	4

The outcome of the software implementing ULSL with pressure ratio as a single variable to estimate the strain trend as shown in Fig. 1 yielded a total mismatch between the measured data plot and the estimated data plot. The statistical analysis of the strain data generated by ULSL resulted in an RMS error of 35% as tabulated in Table VIII. The total mismatch in the plot coupled with a high RMS error resulted in rejection of ULSL for implementation. The outcome of the software implementing ULSQ with pressure ratio as a single variable to estimate the strain trend as shown in Fig. 2 also yielded a total mismatch between the measured data plot and the estimated data plot. The statistical analysis of the strain data generated by ULSQ

resulted in a slightly lesser RMS error of 27% as tabulated in Table VIII. The total mismatch in the plot coupled with a high RMS error resulted in rejection of ULSQ for implementation. The outcome of the software implementing BLSL with pressure ratio and speed as two variables to estimate the strain trend as shown in Fig. 3 also yielded a high mismatch between the measured data plot and the estimated data plot. The statistical analysis of the strain data generated by BLSL resulted in an RMS error of 26% as tabulated in Table VIII.

The high mismatch in the plot coupled with a high RMS error resulted in rejection of BLSL for implementation. The outcome of the software implementing BLSQ with pressure ratio and speed as two variables to estimate the strain trend is shown in Fig. 4. The statistical analysis of the strain data generated by BLSQ resulted in an RMS error of 12% as tabulated in Table VIII. The drastic reduction in the percentage of RMS error, indicating an improvement over the preceding least square approximation methods and with an improved match between the estimated and the measured strain trend, gave a valuable input that we can obtain a reasonable estimation of the strain trend using the selected parameters.

With the valuable input that a combination of pressure ratio and speed may be deployed for estimating the strain data trend, data mapping was attempted wherein exact match was not feasible deploying the variables speed and pressure ratio. With multiple thresholds set for the pressure ratio, data mapping was attempted to estimate the strain values for each specific speed. The plots corresponding to two threshold values of 0.1 and 0.001 are depicted in Fig. 5 and Fig. 6 respectively showing a much closer match between the estimated and the measured trends when compared with the plots obtained from least square approximation strategy. This was also authenticated by the corresponding statistical analysis which yielded RMS errors of 5.6% and 4.5% respectively.

Least Squares approximation tends to provide a curve that approximates the actual measured data whereas interpolation is the process of drawing a smooth curve through the actual measured data points. For certain combinations of speed and pressure ratio, the corresponding strain data could not be traced in the reference files due to the absence of exact match. This data mapping constraint was handled by obtaining the strain data within the set threshold limits for the pressure ratio at a specific speed. Arriving at an optimal threshold value was also a bottleneck in implementing the data mapping with threshold technique. To overcome the above stated limitations of the least square approximation as well as the data mapping with threshold, interpolation methodology was tried out.

The piecewise Linear Interpolation technique has been tried out to improve the goodness-of-fit and achieve a better match between the estimated trend and the measured trend. With a steep reduction in the RMS error to 4% as in Table VIII, coupled with a much closer match between the estimated and the measured trends as in Fig. 7, the interpolation method was considered feasible for implementation. The estimated strain data from interpolation was also subjected to statistical process acceptance. Proof of concept established using data from ten test trails, along with the estimated data set embedded confidence to finalize on the interpolation methodology for implementation to fill the holes in the strain data measurement. The software with this implementation is being used for obtaining the missing strain data trend enabling smooth test trials leading to progressive Research.

VII. CONCLUSION

Health parameter trend being the backbone for assessing the RUL of engine components, its non-availability due to gaps in the acquired health parameter data, posed a set-back to the engine development program. To mitigate this issue,

health parameter trend regeneration was initiated by attempting to estimate the missed out data by establishing a relationship between the health parameter and other performance parameters. In this process, data fusion software was developed to amalgamate the test trial data acquired from multiple systems at varied bandwidths. The combined data was used to try out various methodologies in order to estimate the health parameter and obtain its trend. The trend thus generated when compared with the measured data trend yielded the closeness-of-fit. The RMS error depicted the deviation between the measured data and the estimated data. The developed software was tested with the strain data as a case study. The outcome of various methodologies concluded that interpolation with a combination of parameters (speed and pressure ratio) yielded the least RMS error of 4% coupled with a close match between the estimated and measured trend emerging as an apt choice for implementation. Further when the chosen methodology was subjected to statistical process acceptance, the emerged in-control response served as a proof of concept enabling confident usage of the software to fill the holes in the health parameters to support the engine development. In this paper efforts have been made to estimate the strain data trend using engine speed and pressure ratio which is derived using inlet and outlet pressures. This work can be extended in future to pursue the feasibility of attempting the estimation of the strain data trend using additional parameters. The same concept can be further extended for estimation of trend pertaining to other health parameters, and also for other engine components, to assess their RUL.

ACKNOWLEDGEMENT

The author is grateful to Director GTRE for permitting to present this work. The author is thankful to Shri. Sreelal Sreedhar, Sc 'H' (AD(R&QA), Shri. B.V.A.Patnaik, Sc 'G' TD(SMG,EHLA), Smt. Banumathy. K, Sc 'G,' Shri. Prakash Kumar Yadu, Sc 'E,' and Miss. Sonal Shekhawat, JRF, for their continual support in pursuing this activity.

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