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***Research paper***


# The Need to Evaluate Reliability Based Fatigue Data Analysis

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**Abstract**

This study focuses on an expert system for calculating the variable loading amplitude to predict the fatigue life and reliability analysis of Gumbel distribution. The expert system can provide an effortless way to perform all analyses in one time. This system can alsobe used to analyse reliability on other distributions, including normal, lognormal, Weibull and Gumbel distribution. The poor ability to analyse an interface with many utility software packages is thus addressed. Strain data signals are calculated using empirical-mode decomposition algorithm. The decomposed signals are sifted into a number of intrinsic mode functions (IMFs) until the signals stop and only shortened signals remain. The total cumulative damage and fatigue-life prediction for decomposed signals are further analysed. The expert system also calculates the statistical parameters. The decomposed signals are then examined based on the reliability model, which can produce the probability density, cumulative distribution and reliability functions. The highest frequency signal is the first intrinsicmode function (IMF 1), with $2.84 \square 10^{-5}$ total damage and $3.52 \square 10^{4}$ cycles for fatigue life of the Coffin-Manson strain-life model. Overall, the developed expert system can enable integrated analysis and produce reliable analysis performance.

***Keywords***: *cumulative damage; decomposition; expert systems; fatigue life; reliability*

## 1. Introduction

Fatigue-life prediction is important in the component of automobiles for their safety and reliability. However, reasonably predicting fatigue life requires advanced expertise. The utilisation of an expert system to solve complicated engineering problems, such as fatigue-life prediction, has been already well emphasised [1]. Recently, numerous high-performance and expert systems have been developed to successfully apply in various fields.

Empirical-mode decomposition (EMD) is a main method in Hilbert–Huang transform (HHT), which can reduce a signal into a collection of intrinsic mode functions (IMFs) with a 'well-behaved' Hilbert transform. This method is suitable for nonlinear and nonstationary behaviour signals. EMD is intuitive, direct, adaptive and widely used. Singh [2] and Yang et al. [3] utilized this method in mechanical fault diagnosis. Kim and Song [4] developed an expert system that can predict the fatigue crack initiation life under variable loading. They discussed and evaluated the estimation methods associated with fatigue-life prediction. The Gumbel distribution is a combined model of log-Weibull and double exponential distributions and is also known as extreme value distribution. The Gumbel distribution was popular in ship structures and systems to quantify the probability of failure.

In this study, an expert system is developed for fatigue-life prediction and reliability analysis by using a good, reasonable used. In the past, the analysis has been performed through different techniques. The performance of expert systems is discussed, using strain data of coil spring collected from the campus road test. The system demonstrates all the analyses previously provided.

## 2. Development of reliability

The process of developing the expert system for fatigue-life prediction and reliability analysis is divided into three phases, namely, Phases I–III, as shown in Error! Reference source not found. The details for each phase are as follows:

- Phase I: Characterisation of signal and mechanical properties
- Phase II: Fatigue analysis and global statistical parameters
- Phase III: Reliability analysis

### 2.1 PHASE I: Characterisation of signal and mechanical properties

**Figure 2** shows the flow of Phase I. The strain signal is collected. The mechanical properties are inserted. The signal is decomposed using the decomposition technique of HHT, namely, EMD. These decomposed signals are defined by the algorithm shown in the methodology section, where the decomposition method is also presented. The expert system used the decomposed signal to determine the characteristics of all decomposed signals.

In this study, SAE5160 carbon steel was used as the component material due to its common usage in automotive industries for the fabrication of coil springs. **Table 1** shows the mechanical properties for SAE5160 carbon steel [5].

In this step, a load history is inputted, and the strain data are collected. The strain signal of the campus road (Error! Reference source not found.), which was collected in 60 s, was used. The strain gauge was attached to the coil spring of a sedan car. The test used the sampling frequency of 500 Hz with 30,000 data points.

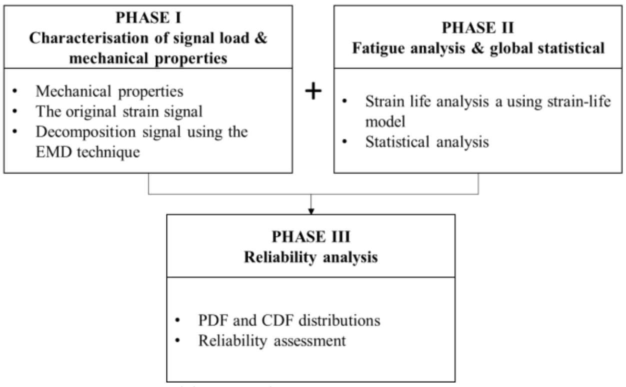



**Fig. 1:** Phase of fatigue life prediction and reliability analysis


**Fig. 2:** The flow of phase I

**Table 1:** Mechanical properties of SAE5160

| Properties | Values |
|---|---|
| Ultimate tensile strength (MPa) | 1,584 |
| Material Modulus of elasticity (GPa) | 207 |
| Fatigue strength coefficient (MPa) | 2,063 |
| Fatigue strength exponent | -0.08 |
| Fatigue ductility exponent | -1.05 |
| Fatigue ductility coefficient | 9.56 |

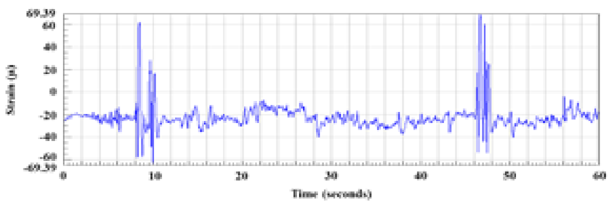



**Fig 3:** Strain signal of campus road

The strain signal is divided into a number of IMFs through EMD. The decomposed signals showed that a function to have physically meaningful instantaneous frequency, the IMFs are zero mean of oscillation signals that should satisfy both conditions; (i) the number of extreme and zero crossings must either be equal or differ at most by one and, (ii) at any point, the mean value of the envelope defined by local maxima and minima is zero [6]. This condition is indicated by the signal $x(t)$ to be analysed. The EMD method are extracted and calculated by the HHT algorithm. The IMFs exist through the following sifting process:

i. The local maxima and minima of the signal $x(t)$ are identified.
ii. The cubic spline interpolates the extreme point from the upper and lower envelope.
iii. The mean $m(t)$ of the signal needs to be calculated as the average of the upper and lower envelops.
iv. $h(t) = x(t) - m(t)$ needs to be computed.
v. An IMF will stop if the sifting result is $h(t)$. Then, $h(t)$ is set as the signal and iterated on $h(t)$ through steps i–v. The stopping condition is as follows:

$$\sum_t \frac{\left[h_{k-1}(t) - h_k(t)\right]^2}{h_{k-1}^2(t)} < SD \quad (1)$$

where $h_k(t)$ denotes the sifting result in the $k$-th iteration. This process stops when the slowly varying residual function has no more oscillations.

## 2.2 PHASE II: Fatigue analysis and global statistical parameters

In Phase II, the fatigue life analysis is obtained using the strain-life model on the basis of mean stress effect. This analysis can calculate the relevant cumulative damage rules and the parameters statistically computed for each decomposed signal to determine the behaviour signals. The fatigue life assessment for the strain-life model is applied with the strain-life fatigue damage model. This strain-life model can be used for applications involving the effects of the mean stress. The relationship between strain and life is presented as follows:

Coffin-Manson:

$$\varepsilon_a = \frac{\sigma'_f}{E}\left(2N_f\right)^b + \varepsilon'_f\left(2N_f\right)^c \quad (2)$$

SWT:

$$\sigma_{\max}\varepsilon_a = \frac{\left(\sigma'_f\right)^2}{E}\left(2N_f\right)^{2b} + \sigma'_f\,\varepsilon'_f\left(2N_f\right)^c \quad (3)$$

Morrow:

$$\varepsilon_a = \frac{\sigma'_f}{E}\left(1 - \frac{\sigma_m}{\sigma'_f}\right)\left(2N_f\right)^b + \varepsilon'_f\left(2N_f\right)^c \quad (4)$$

where $E$ is the material modulus of elasticity; $\varepsilon_a$ denotes a true strain amplitude; $2N_f$ refers to the number of reversals to failure; *b* and *c* represent the fatigue strength exponent and fatigue ductility exponent, respectively; $\varepsilon'_f$ indicates the fatigue ductility coefficient; $\sigma'_f$ signifies the strength coefficient; $\sigma_m$ stands for the mean stress; and $\sigma_{\max}$ symbolizes the maximum stress.

The fatigue damage for each loading cycle $D_i$ can be calculated as follows:

$$D_i = \frac{1}{N_f} \quad (5)$$

The Palmgren-Miner rule is then used to calculate the cumulative fatigue damage *D* of a variable amplitude loading, which is defined as follows [7]:

$$D = \sum\left(\frac{n_i}{N_f}\right) \quad (6)$$

where $n_i$ is the number of cycles at the stress level.

The global signal statistical parameters are widely used for random signal classification and pattern monitoring. For a signal *F* with the number of data *n*, the mean value $\bar{x}$ is given by:

$$\bar{x} = \frac{1}{n}\sum_{j=1}^{n} F \quad (7)$$

Standard deviation (SD) measures the distribution of a data set on the basis of the mean value. The SD for a number of sampling data *F* can be expressed as follows:

$$SD = \sqrt{\frac{1}{n}\sum_{j=1}^{n}\left(F - \bar{x}\right)^2} \quad (8)$$

The variance is calculated as follows,

$$\text{var} = \frac{(X - \bar{x})^2}{n} \tag{9}$$

where $\bar{x}$ is the mean, $n$ denotes the total number of data and $X$ represents the data value.
The r.m.s. is the second statistical moment used to determine the total energy contained in a signal. The r.m.s of discrete data can be calculated as follows:

$$r.m.s. = \left\{ \frac{1}{n} \sum_{j=1}^{n} x_j^2 \right\}^{1/2} \tag{10}$$

Skewness is the third statistical moment used to measure the symmetry of the data distribution on the basis of the mean value. The skewness of a signal $F$ can be expressed as follows:

$$Skew = \frac{1}{n(SD)^3} \sum_{j=1}^{n} (F - \bar{x})^3 \tag{11}$$

Kurtosis is the fourth statistical moment, which is sensitive to spikes, and represents the continuity of peaks in a time series loading. Kurtosis $K$ for a set of discrete data $F$ is formulated as follows:

$$K = \frac{1}{n(SD)^4} \sum_{j=1}^{n} (F - \bar{x})^4 \tag{12}$$

### 2.3 PHASE III: Reliability analysis

In Phase III, on the basis of the decomposed signals, the reliability model is developed to determine the difference in the signal trend of the probability density function (PDF), cumulative distribution function (CDF) and reliability function of the Gumbel distribution.

The system calculates the function of the Gumbel distribution. This distribution shows the tabulation data of the PDF, CDF and reliability function of each decomposed signal. The distribution is presented as follows:

PDF:

$$f(x) = \frac{1}{\sigma} \exp\left[ \frac{1}{\sigma}(x - \mu) - \exp\left( \frac{x - \mu}{\sigma} \right) \right] \tag{13}$$

CDF:

$$F(x) = 1 - \exp\left[ -\exp\left( \frac{x - \mu}{\sigma} \right) \right] \tag{14}$$

Reliability function:

$$R(x) = \exp\left[ -\exp\left( \frac{x - \mu}{\sigma} \right) \right] \tag{15}$$

where $\sigma$ and $\mu$ are the scale and location parameters, respectively. The random variables for the Gumbel distribution with the location and scale parameters are $-\infty < \mu < \infty$ and $\sigma > 0$, respectively.

Error! Reference source not found. shows the interface of the expert system in which the real data, material properties and stress converter (if needed) are inserted. Moreover, the life prediction of the signal is presented. One of the parts displays the statistical parameters. The last part is where the needed reliability model can be selected.

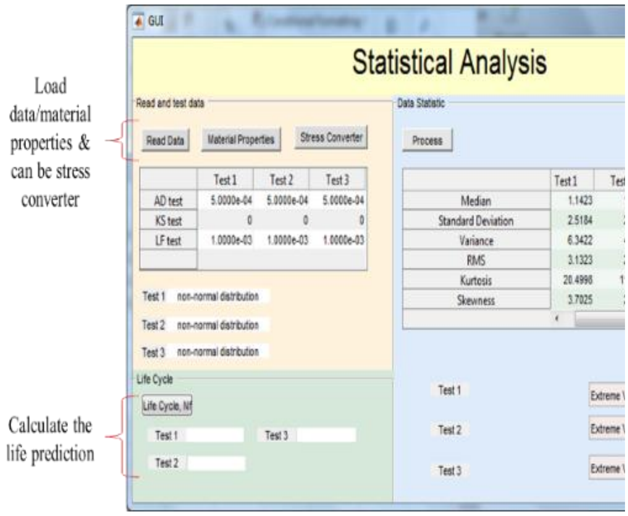



**Fig 4:** Interface of the expert system

## 3. Results and discussion

The original signal of the campus road was decomposed into a number of IMFs on the basis of the HHT algorithm, empirical mode decomposition (EMD). Error! Reference source not found. presents the results obtained from EMD with the IMF component from the campus road signal. Error! Reference source not found. only shows the high frequency (IMF 1 to IMF 4) of the decomposed signal.
Each IMF has a distinctive amplitude and frequency content. The decomposed signal represents local oscillations from the longest period signal to the shortest period signal [8]. These IMFs have two important properties: (i) each IMF is a zero-mean function by construction, and (ii) for all practical purposes, the consecutive IMFs can be locally orthogonal to each other. At the same time, the decomposed signal changes to high frequency (IMF 1 to IMF 4). The signal conditions are due to the information nature of the IMFs. The intrinsic oscillations emerge naturally. On the basis of the knowledge about the monitored phenomena, solid conclusions can be obtained about the meaning of each mode and its relation to some behaviours.

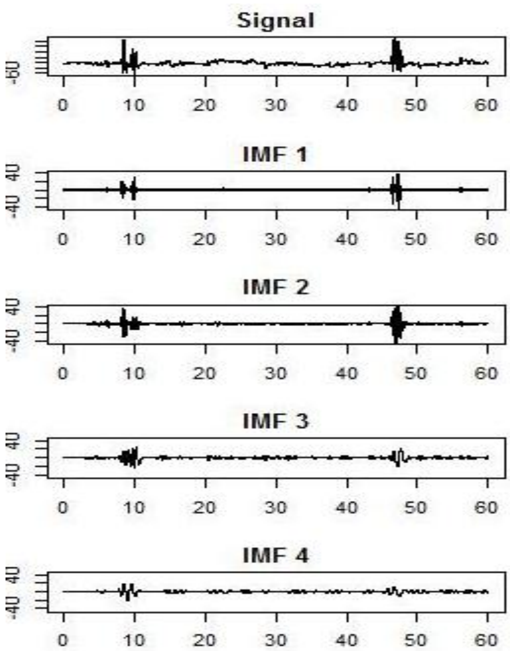



**Fig 5:** EMD of campus road signal

A remarkable advantage of the decomposition is that directly observing the local condition in the fatigue data signal is possible. In the expert system, either type of the strain-life model, i.e. Coffin–

Manson, SWT or Morrow, can be selected to calculate the total damage and fatigue life. **Table 2** shows the total damage and fatigue-life prediction values for each decomposed signal. The fatigue damage and fatigue life are calculated using the strain-life mean stress effect models, namely, Coffin-Manson, SWT and Morrow.

The expert system helps to calculate the statistical parameters presented in **Table 3.** The system calculates the statistical parameters, i.e. mean, SD, variance, r.m.s, kurtosis and skewness, on the basis of the input of the signal.

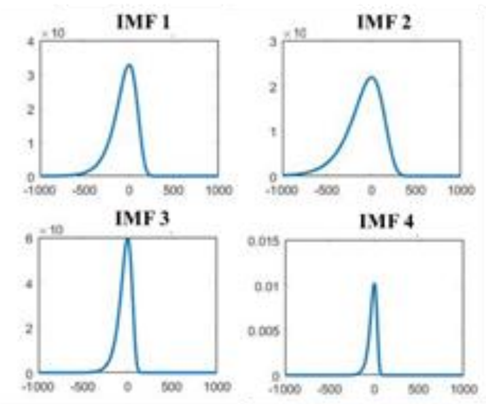
**Table 2**: Total damage and fatigue-life prediction values

| IMF | Coffin-Manson | | SWT | | Morrow | |
|---|---|---|---|---|---|---|
| | **Fatigue life (cycles)** | **Total damage** | **Fatigue life (cycles)** | **Total damage** | **Fatigue life (cycles)** | **Total damage** |
| **1** | $3.52\times10^{4}$ | $2.84\times10^{-5}$ | $4.06\times10^{4}$ | $2.46\times10^{-5}$ | $3.99\times10^{4}$ | $2.51\times10^{-5}$ |
| **2** | $3.51\times10^{4}$ | $2.85\times10^{-5}$ | $3.98\times10^{4}$ | $2.51\times10^{-5}$ | $3.92\times10^{4}$ | $2.55\times10^{-5}$ |
| **3** | $3.50\times10^{4}$ | $2.86\times10^{-5}$ | $3.46\times10^{4}$ | $2.89\times10^{-5}$ | $3.47\times10^{4}$ | $2.88\times10^{-5}$ |
| **4** | $3.52\times10^{4}$ | $2.84\times10^{-5}$ | $5.07\times10^{4}$ | $1.97\times10^{-5}$ | $4.83\times10^{4}$ | $2.07\times10^{-5}$ |

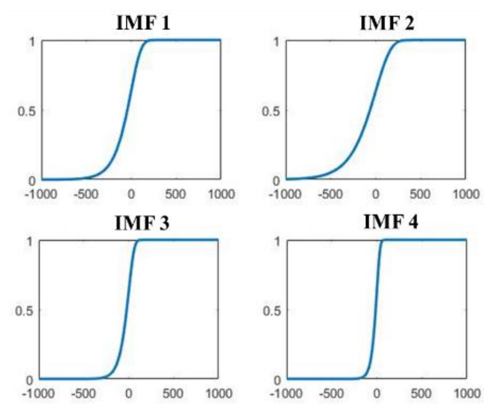
**Table 3**: Values of the statistical parameters

| IMF | 1 | 2 | 3 | 4 |
|---|---|---|---|---|
| **Mean** | 0.76 | 1.72 | 2.04 | 1.86 |
| **SD** | 3.29 | 4.81 | 3.52 | 2.52 |
| **Variance** | 10.79 | 23.11 | 12.41 | 6.34 |
| **r.m.s** | 3.37 | 5.12 | 4.07 | 3.13 |
| **Kurtosis** | 60.62 | 33.86 | 16.82 | 20.50 |
| **Skewness** | 7.10 | 5.26 | 3.59 | 3.70 |

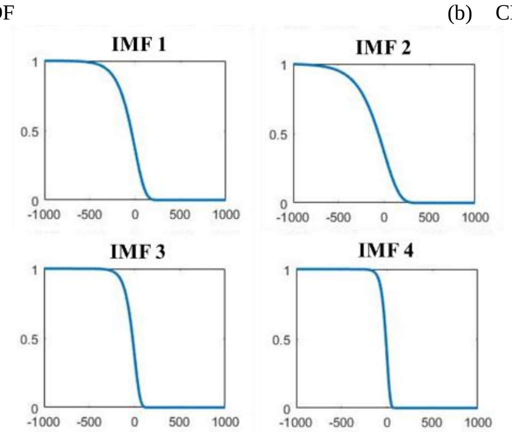
Statistical methods are used to determine the reliability using the decomposed signal of strain data. The probability methods are used to determine the system reliability using the knowledge of reliability. Gumbel distribution was in two parameters and it more accurate estimate than three parameters [9]. **Figure 6** shows the pattern of the reliability analysis for each decomposed signal. The reliability analysis was calculated by Equations (13), (14) and (15). **Figure 6(a)** show that PDF completely was skewed to the left. PDF of Gumbel distribution has no shape parameter, and this means that PDF only have one shape which it does not change. **Figure 6(b)** was the CDF pattern of Gumbel distribution. **Figure 6(c)** shows the reliability which the life of the components that experience very quick wear out after reaching the certain age [10].




(a) PDF




(b) CDF




(c) Reliability curve

**Fig 1:** Reliability analysis for each decomposition signal

## 4. Conclusion

The expert system is developed to show an excellent performance for the decomposed signal data on the basis of the fatigue data analysis. The expert system is easy to use with one system, which can analyse the data at one time. This expert system was in moderate between ± 20 of total damage and fatigue-life prediction. The characteristics of the decomposed signal in this expert system show the statistical parameters for each decomposed signal, which can define the behaviour of each IMF itself. The basic reliability of the Gumbel distribution shows the differences in the pattern of skewness for PDF, CDF and reliability function.

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