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Evaluation of Reliability-based Fatigue Strain Data Analysis for an Automobile Suspension Under Various Road Condition

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Abstract: This work aimed to analyse fatigue-based reliability for automobile suspension on the basis of the strain load signal from an automobile under operating conditions. Fatigue life was used to ensure the aging of the component, and it was suitable for use for longer than the standard age given. The damage behaviour patterns for each retained edited signal from 100% to 85% were used to predict the fatigue durability of the suspension with a sampling frequency of 500 Hz for various road conditions. The extended global statistics were computed to determine the behaviour of the signal. Accelerated durability analysis was used to remove the low-amplitude cycles, which contributed minimally toward the total damage, by considering the effects of mean stresses. The reliability assessment, hazard rate function and mean time-to-failure (MTTF) based on the retention signal were predicted through fatigue strain data analysis. Changes were observed from a range of below 15% and above 60% of the length of the actual original signals due to the low amplitude. Extended global statistics showed scale parameter of 75 and 94 with an MTTF of 1.25×10^3 and 1.27×10^3 cycles. The retention signal loads provide an accurate signal editing technique for predicting fatigue life with good reliability characteristic understanding for the suspension part.

Keywords: damage, fatigue, hazard rate, reliability, Gumbel distribution

1. Introduction

Failure in such mechanical components as vehicle suspension systems is widely used in the automotive industry. Several researchers have studied suspension systems and analysed the compression of coil spring fracture at the transition position for the bearing coil. Radiation ridges have been observed to emanate from wear scars [1]. Several researchers investigated the fatigue behaviour of springs and found short surface fatigue cracks from the origin [2]. In the literature on fatigue assessment, many researchers have developed techniques for identify the fatigue life and preventing fatigue failure [3]. Fatigue life assessment in retain signal to summarises fatigue data by removing low-amplitude cycles to reduce the duration time test. Two factors have been suggested to ensure that fatigue performance achieves efficient design and modification processes. DuQuesnay mentioned that the component test should be as short as possible for maximum accuracy [4]. Several techniques, such as short-time Fourier transform (STFT) and wavelet transform, have been developed for time and time-frequency analyses [5]. Then, Mahdavi et al. [6] was analysed the features extraction based on Wavelet transform and following with Jamaluddin et al. [7] doing the detection using two electrodes system device with Wavelet analysis. Some of the techniques developed were used for removing low-amplitude cycles to retain high-amplitude cycles [8].

Random variable help is used to characterise stress or strain behaviour and thus classify fatigue data [9]. Putra et al. [10] used clustering analysis to study the segment behaviours of fatigue data, and the segment extraction of clustering optimised the data signal. In signal processing, fatigue extraction analysis contributes to scattered data signal and behaviour. In fatigue-based reliability assessment, the Weibull distribution is suitable for this case and can describe the mean stress effect [11]. This distribution helps in the observation of component age until failure. Knowing the failure rate is important in the contexts of style of uses and maintenance of components. The Weibull distribution is well known in predicting the lifetime uses of components, especially in the automotive industry [12], and several researchers have used this distribution. Tinga used the Weibull distribution to manage usage on the basis of maintenance and the system, thereby increasing prediction accuracy [13]. Jiang and Murthy observed that the effect of the shape parameter on the failure rate can improve the reliability and maintenance of the component [14] in the same distribution. The Weibull distribution has also been used in reliability and stress

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distribution, in which a high value of the shape parameter shown strength [15].

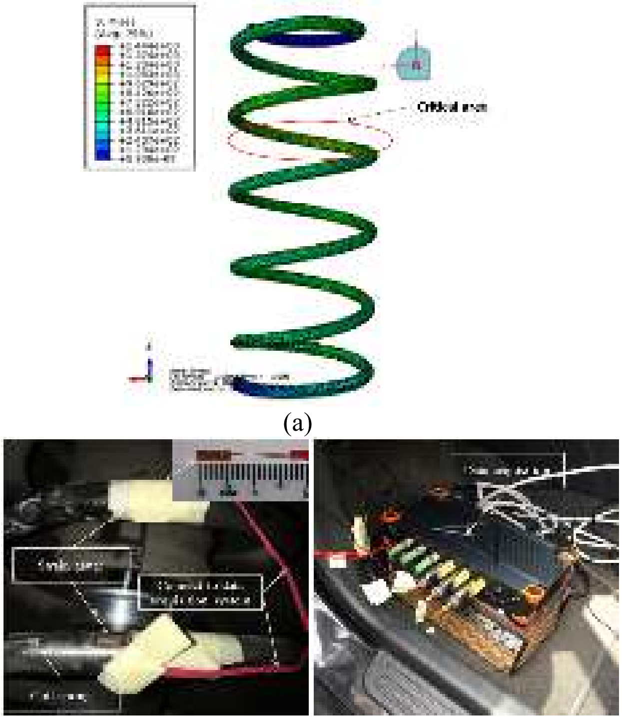
Gumbel distribution or extreme value distribution is used in engineering and comprises two distributions, namely, log-Weibull and exponential distributions. This reliability model (Gumbel) is used to model the distribution of the maximum or minimum of a number sample to various distributions and to estimate the strength of materials and predict the lifetime of components. This distribution has been used in the marine pitting corrosion of steel to estimate the aging of a pipe [16]. Asadi and Melchers [17] used the Gumbel distribution to present the statistics of maximum pit depth and estimate the probability of pipe wall perforation.

In this work, we study the reliability through fatigue-based retention signal which are selected interval range with 5% between 100% until 85% retention signal. These retention signals help improve lifetime prediction for shortened time signals and can estimate the aging of components. From the original signal, the low-amplitude cycle is eliminated, and the high-amplitude cycle is retained by producing a new signal. The original and retained signals can potentially produce the extended statistics and show minimal difference in the fatigue life value with each model. The reliability of the retention signal is determined in the reliability assessment. Therefore, the relationship of location and scale parameter with life prediction is important for reliability assessment because it describes the characteristics of the data.

2. Methodology

Fatigue data was measured from the coil spring of suspension of a sedan car. The highest stress area of coil spring for suspension system was in the red circle shown in Fig. 1(a) [18]. In previous studies, Putra et al. were obtained the stress concentration experienced through the FEA (Finite Element Analysis). He finds that the highest stress area on coil spring was provided with colour contour which the area occurs with 1.4 kPa of maximum pressure [18]. A 2 mm strain gauge was placed on the most critical part which has the highest stress location on the suspension coil spring shows in Fig. 1(b) and Fig. 1(c). This work used two types of roads, rural and urban, as shown in Fig. 2. The car was driven at velocities of 30 and 70 km/h on the rural and urban roads, respectively. The signals were 120 s in length, comprised 60,000 data points. From data acquisition system the sampling rate can adjust with some sample rate values, 500 or 1000 Hz and the sampling rate was selected 500 Hz because it more appropriate for the on-site of data collection [18].

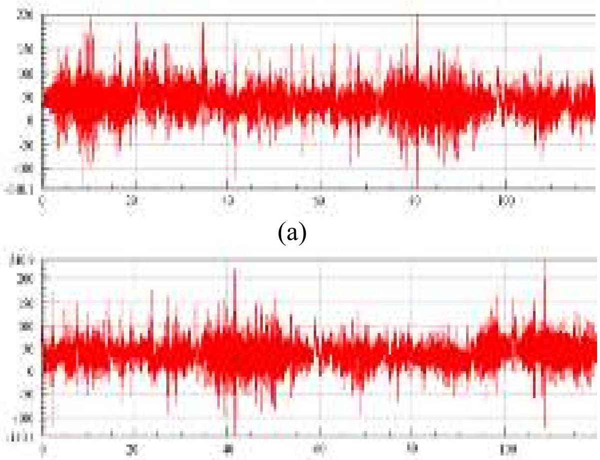
The detailed steps of this work are illustrated in Fig. 2. This study consisted of five steps. Step 1 was related to the time histories and performance of the strain signal. The strain signals used were collected on the test road. Step 2 represented the signal retention with 5% interval between 100% to 85%. Step 3 involved the strain–life model, which can predict the fatigue life and the cumulative damage of signals through calculation. In Step 4, statistical parameters, such as content mean, standard deviation, skewness variance and kurtosis, were calculated. The last step, Step 5, involved the reliability analysis of the aging component. The probability density function (PDF), cumulative distribution function (CDF), reliability function, hazard rate function and mean-time-to-failure (MTTF) were determined in this step.



(a)

(b) (c)

Fig. 1 Road test of automobile; (a) stress concentration at coil spring, (b) strain gauge attached to coil spring, (c) strain data collection equipment.



(a)

(b)

Fig. 1 Signal collected; (a) rural (b) urban.

2.1 Damage retention form signal retention technique

The signal underwent fatigue data editing for the removal of low-amplitude cycles. The technique approached the high-amplitude event where most damages were retained to produce a shortened loading for the time series, and the relevance to fatigue analysis contained information. Time-domain editing techniques were developed to move the time segments, which used time-correlated fatigue damage analysis. This method was used to remove the non-damaging sections of the time history on the basis of the fatigue damage windows of the input signal. The techniques approached the damage signal to divide it into several time segments. Each time window contained a short segment of time calculated by the fatigue damage. The minimal-damage windows were removed to retain most of the fatigue damage. These windows were assembled to produce a shortened signal for the durability analysis, and this process is shown in **Fig. 3**. Using this approach, 100% until 85% damage retention was set as the editing target to maintain the phase and amplitude of the original signal.

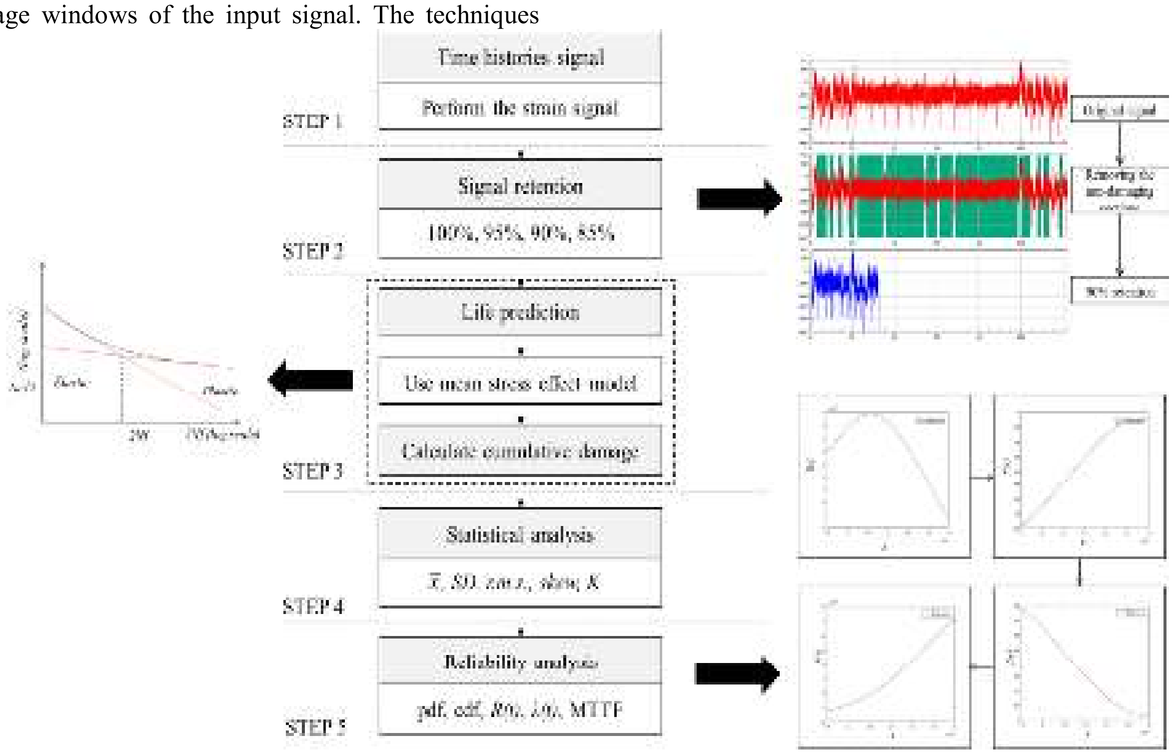
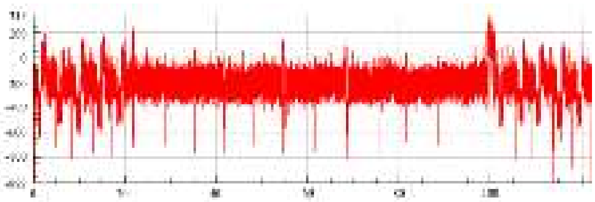
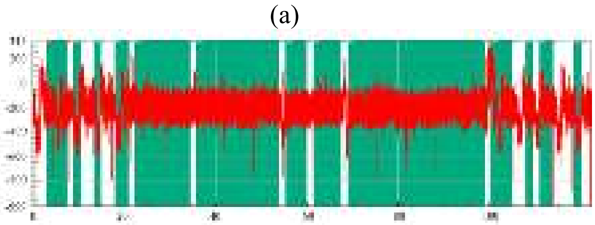


Fig. 2 Flowchart of methodology



(a)



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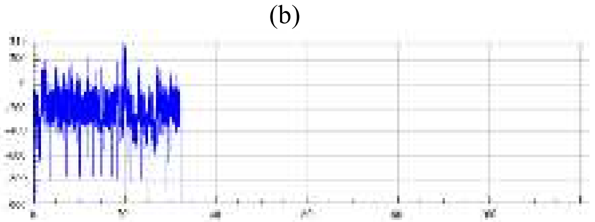

(c)

Fig. 3 Retention process; (a) original signal, (b) segment with non-damaging sections removed, (c) retained signal after 90% retention.

The strain life approach is sufficiently accurate for fatigue life assessment because it considers plastic forming events existing in local areas to determine the strength of components. The strain life approach is usually applied to ductile materials because the low fatigue cycles of small components, which are within only 10^3 cycles, do not require high operating costs and do need extensive crack observation where the failure occurs [18].

The Coffin–Manson (CM), Morrow (M) and Smith–Watson–Topper (SWT) strain life models are applied with strain life fatigue damage models in fatigue life prediction. The Morrow model is a reasonable approach for steel, whereas SWT provides satisfactory results in a wide range of materials and is thus an appropriate choice for general use. Meanwhile, the relationship for Coffin-Manson is as follows:

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

The M strain life model is mathematically defined as follows:

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

The SWT strain life model is defined according to the following formula:

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

where E is the material modulus of elasticity, ε_a is a true strain amplitude, $2N_f$ is the number of reversals to failure, b is the fatigue strength exponent, c is the fatigue ductility exponent, ε'_f is the fatigue ductility coefficient and σ'_f is the fatigue strength coefficient. Meanwhile, σ_m is the mean stress and $\sigma_{\max}$ is the maximum stress, represented in Equations (2) and (3). The fatigue damage for each loading cycle D can be calculated as follows:

$$D = \frac{1}{N_f} \quad (4)$$

The Palmgren–Miner's linear damage rule is used to calculate the cumulative fatigue damage for a variable amplitude loading cycle as follows:

$$D = \sum\left(\frac{n_i}{N_f}\right) \quad (5)$$

where n_i is the number of cycles at stress level.

2.2 Statistical signal analysis

Statistical signal parameter is used for random signal classification to retain the originality of the signal behaviour [19]. For signal, F with the number of data n, the mean value $\bar{x}$ is given by the following:

$$\bar{x} = \frac{1}{n}\sum_{j=1}^{n} F \quad (6)$$

The standard deviation (*SD*) measures the distribution of the data set on the basis of the mean value and is expressed as follows:

$$SD = \sqrt{\frac{1}{n}\sum_{j=1}^{n}\left(F-\bar{x}\right)^2} \quad (7)$$

The third statistical moment is skewness, which measures the symmetry of a data distribution on the basis of the mean value. The signal F can be expressed by the following skewness (*Skew*) equation:

$$Skew = \frac{1}{n\left(SD\right)^3}\sum_{j=1}^{n}\left(F-\bar{x}\right)^3 \quad (8)$$

The kurtosis is the fourth statistical moment; it is sensitive to spikes and represents a continuation of peaks in a time series loading. The kurtosis (*K*) can be expressed as follows:

$$K = \frac{1}{n(SD)^4}\sum_{j=1}^{n}\left(x_j-\bar{x}\right)^4 \quad (9)$$

2.3 Reliability prediction of the suspension

The Gumbel distribution illustrates the stochastic data behaviour of extreme events found at the tails of probability distributions. Gumbel distribution (Type I) or extreme value distribution can be a model used with a situation of randomness process. This distribution aims to predict probabilities for rare events greater or smaller than previously recorded events. Gumbel distribution is a unimodal distribution with PDF, CDF, reliability function, hazard rate function and MTTF. The PDF and CDF of the Gumbel distribution are represented as follows [20]:

PDF:

$$f(N_f) = \frac{1}{\beta}\exp\left[\left(N_f-\mu\right)-\exp\left(\frac{N_f-\mu}{\beta}\right)\right] \quad (10)$$

CDF:

$$F\left(N_f\right) = \exp\left\{-\exp\left(-\left(\frac{N_f-\mu}{\beta}\right)\right)\right\} \quad (11)$$

The standard Gumbel distribution also has the reliability function, which serves as a survival component, and hazard rate function, which is the number of failures per unit time that can occur for the product. These functions are represented as follows:

Reliability function:

$$R\left(N_f\right) = 1-\exp\left[-\exp\left(-\frac{N_f-\mu}{\beta}\right)\right] \quad (12)$$

Hazard rate function:

$$h\left(N_f\right) = \frac{1}{\beta}\exp\left(-\frac{N_f-\mu}{\beta}\right) \quad (13)$$

The mean-time-to-failure (MTTF) is the average time of failure-free operation up to a failure event calculated from a homogeneous lot component under operation. The MTTF is represented as follows:

$$MTTF = \mu - 0.5776 \quad (14)$$

where β is a scale parameter and μ is a location parameter. The random variable for the Gumbel distribution with location parameter is $-\infty<\mu<\infty$, and the scale parameter is $\beta>0$.

Table 1 Retention percentage and time values retained

Road	Retention (%)	Time (seconds)	Reduction (%)	Retention (%)
Rural	Original	120.0	-	-
	100%	72.0	40.0	60.0
	95%	18.9	84.3	15.8
	90%	14.8	87.7	12.3
	85%	11.3	90.6	9.4
Urban	Original	120.0	-	-
	100%	60.0	50.0	50.0

95%	13.6	88.7	11.3
90%	9.8	91.8	8.2
85%	7.4	93.8	6.2

3. Result and discussions

This section presents and discusses the results and analysis of fatigue life and cumulative damage on the basis of strain data of automobile components. The collected strain signals from the rural and urban test roads were used in this analysis. The signals were collected from the coil spring of a suspension system. The original signal underwent several percentages with 5% interval for each road. The signal retention was between 100% and 85% in the next subsection.

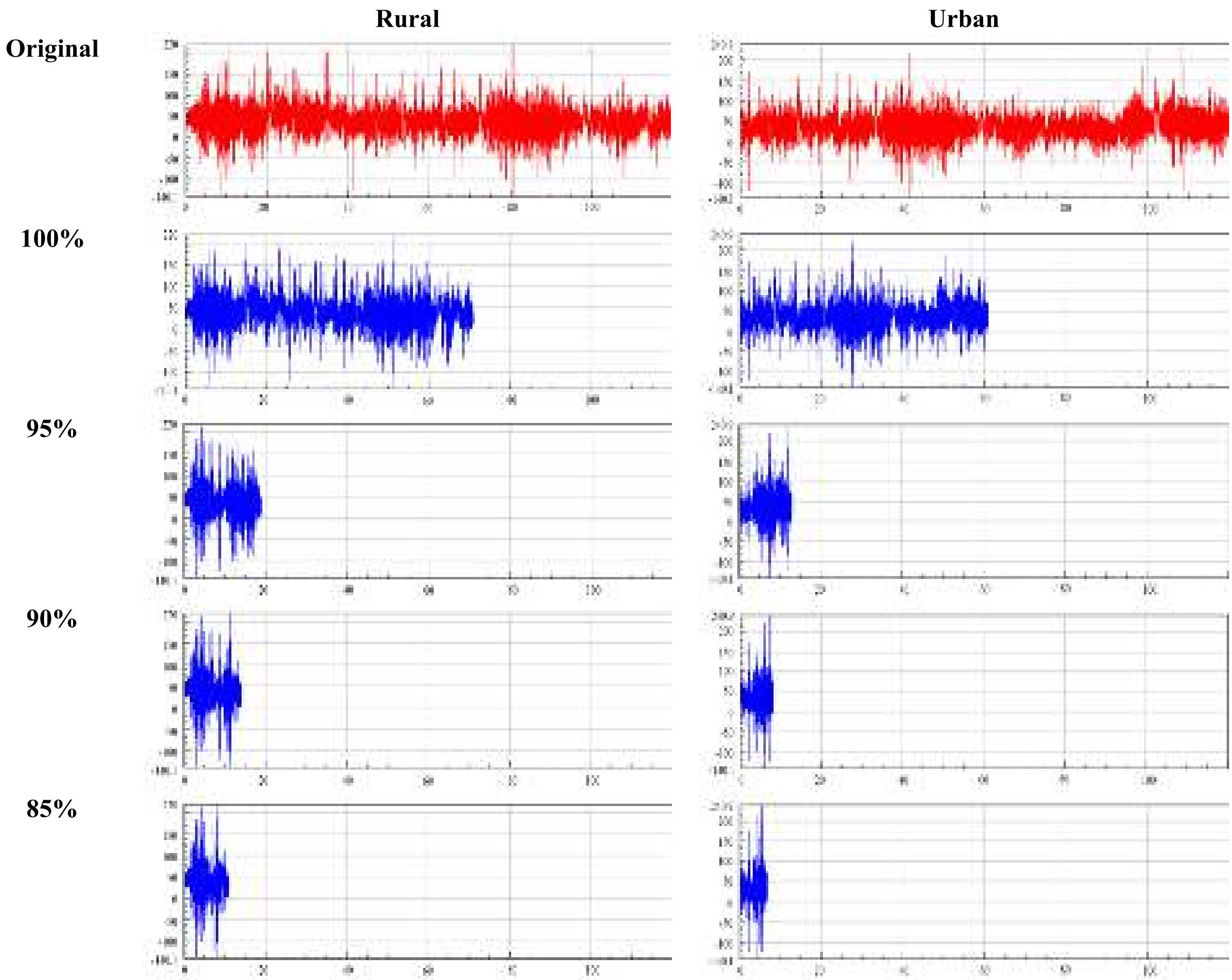

Fig. 4 Differences of retention signals for both roads

Table 1 The total damage and fatigue life predictions during the analysis

Road	Signal	Number of cycles	Coffin-Manson		Morrow		SWT	
			Fatigue life (cycle)	Total damage (/cycle)	Fatigue life (cycle)	Total damage (/cycle)	Fatigue life (cycle)	Total damage (/cycle)
Rural	Original	11302	1090	9.16×10^{-4}	757	1.32×10^{-3}	638	1.57×10^{-3}
	100%	6354	1090	9.16×10^{-4}	757	1.32×10^{-3}	639	1.57×10^{-3}
	95%	1581	1150	8.72×10^{-4}	817	1.22×10^{-3}	702	1.43×10^{-3}
	90%	1196	1200	8.34×10^{-4}	855	1.17×10^{-3}	734	1.36×10^{-3}
	85%	922	1300	7.70×10^{-4}	943	1.06×10^{-3}	813	1.23×10^{-3}
Urban	Original	11435	1110	9.04×10^{-4}	837	1.19×10^{-3}	733	1.36×10^{-3}
	100%	5474	1110	9.04×10^{-4}	838	1.19×10^{-3}	733	1.36×10^{-3}
	95%	1057	1170	8.58×10^{-4}	891	1.12×10^{-3}	786	1.27×10^{-3}
	90%	681	1210	8.34×10^{-4}	926	1.08×10^{-3}	818	1.22×10^{-3}
	85%	558	1240	8.17×10^{-4}	947	1.06×10^{-3}	899	1.20×10^{-3}

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3.1 Signal retention analysis from various road profiles

The results of the retention signal from the rural and urban roads are shown in Fig 5. These findings represent the percentage of the retention signal from the original signal until the 5% interval retention (100%, 95%, 90% and 85%). The retention of all signals will change the minimum value of the total fatigue damage. This condition helps improve fatigue life by removing the low amplitude that appears in the original signal. And this does not significantly affect the original signal because it removes only the minimal fatigue damage potential [5].

Table 1 states the different values for time retention and the percentage of reducing and retaining signals for both road conditions after the signal retention process. The 100% retention retain time to 72.0 and 60.0 seconds for rural and urban. It was reduced 40.0%, 50.0% seconds duration of the signal and retained to 60.0%, 50.0% seconds time signal for rural and urban respectively. While, the lowest retention percent, 85% retention, reduced until 90.6%, 93.8 %, and retained signal to 9.4%, 6.2%-time duration of signals for rural and urban road.

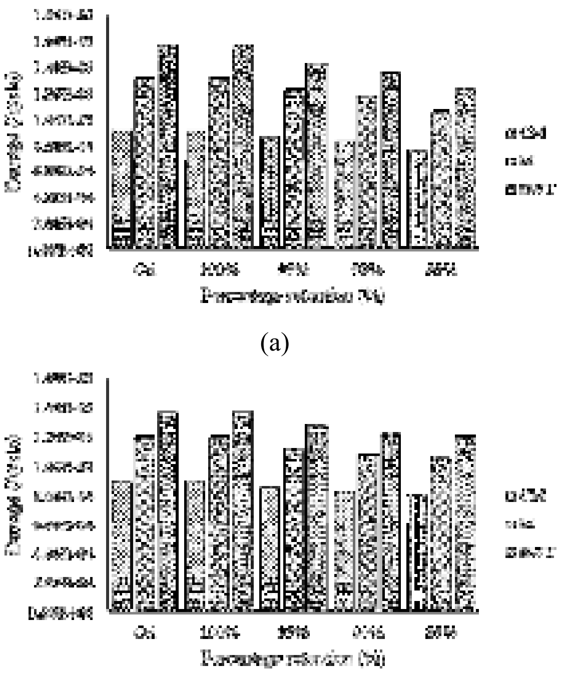
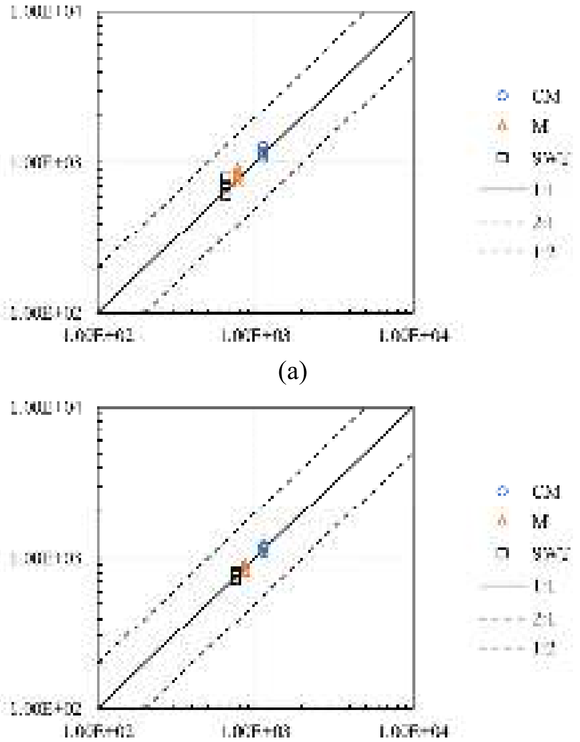


Fig. 5 Differences in damage for both roads: (a) rural, (b) urban

The fatigue damage for all signals of both roads were calculated to study the efficiency on the basis of fatigue damage retention. The fatigue damage was calculated through the strain life model, which applied the Coffin-Manson, Morrow and SWT strain life relationship. The optimum retained signal was determined to be the shortest signal with the minimal fatigue damage deviation when it was compared with the original signal and its retained behaviour. The predicted coil spring fatigue life is shown in Table 2. In the table, the fatigue life calculated by the Coffin-Manson, Morrow and SWT models for the original signal and 100% damage retention for the rural road have nearly the same value as in the original strain signal except for the fatigue life obtained by SWT, which is 639 cycles. The difference between the original signal and the 100% retention is small at only one cycle higher than the original strain signal. The fatigue life for the urban road shows that Morrow has the same difference as that for the rural road, in which the 100% retention has 838 cycles and the original has 837 cycles. The 100% retention is one cycle higher than the original signal. While in Fig. 6 show the difference of total damage for each fatigue damage model (Coffin-Manson, Morrow and SWT).

Table 2 Statistical values for each signal

Type	Signal	K	Skew	Mean	SD	Var
Rural	Original	5.68	0.33	39.59	27.54	758.29
	100%	5.29	0.32	40.47	31.25	976.27
	95%	5.72	0.26	39.86	36.18	1309.33
	90%	5.99	0.33	40.75	36.99	1368.32
	85%	6.54	0.12	38.46	34.94	1220.85
Urban	Original	5.54	0.20	37.37	25.55	652.88
	100%	5.56	0.21	38.22	29.10	846.84
	95%	5.93	0.12	37.17	35.38	1251.99
	90%	6.93	0.23	35.0404	35.95	1292.06
	85%	7.69	0.36	35.13	35.64	1269.97



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(b)

Fig. 6 Correlation between original and retention signals with risk assessment based on fatigue damage: (a) rural road condition, and (b) urban road condition

3.2 Statistical parameters

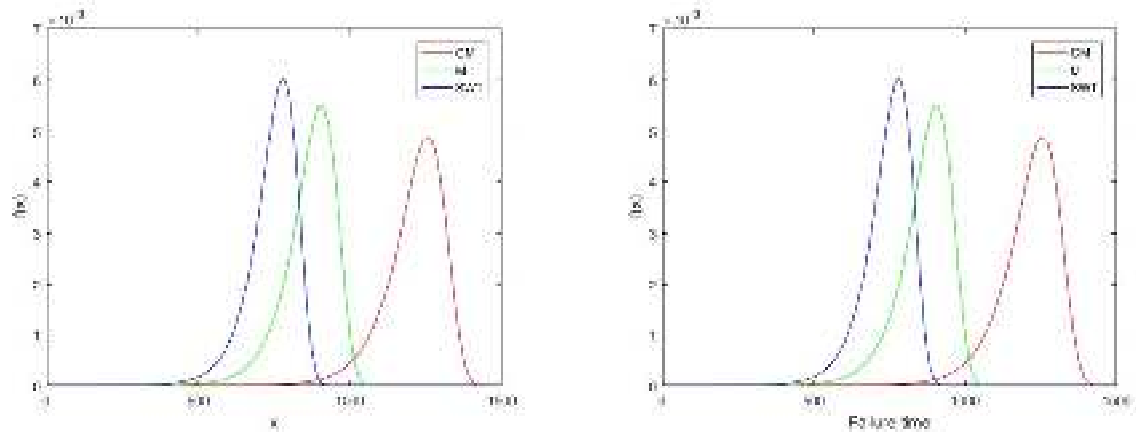
The signals were statistically analysed and are listed in Table 3. The statistical parameters are approximately similar to those in the original signal and the retention for kurtosis. The other parameters, namely, mean, standard deviation and variance, differed by up to 10% from the original signal [21].

In the graphs shown in Fig. 7, was the correlation between the relationship of total damage with differences of fatigue damage model, Coffin-Manson, Morrow and SWT. The total damage for both roads (Fig. 7(a) for rural road and Fig. 7(b) for urban road) with difference of fatigue damage models were distributed between 1:2 or 2:1 correlation. Original and retained signals were extracted on the basis of their own range of total damage. The behaviour of the total damage values for the retained signal with the three fatigue damage models is similar with that for the original signal. The life of retention for all strain life models is between 1:2 and 2:1 boundary when correlated with the life of the original signal.

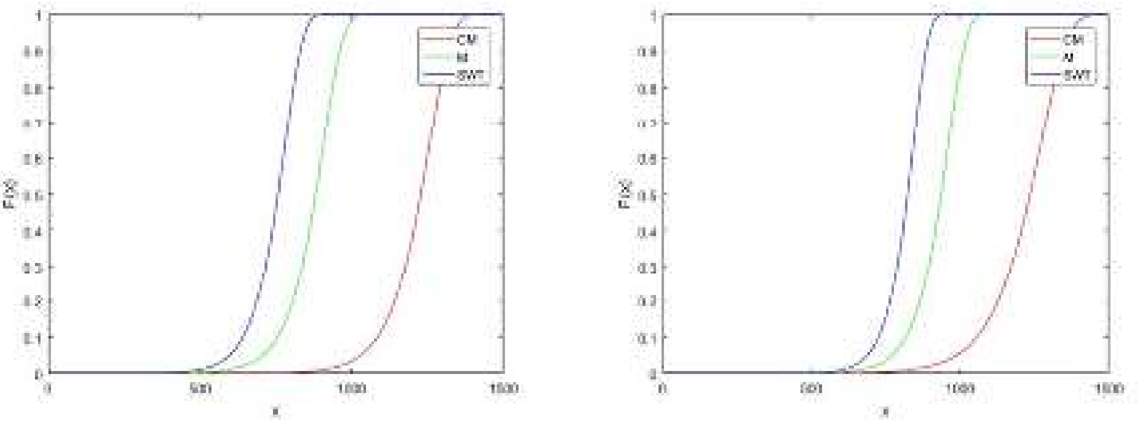
3.3 Reliability prediction for risk assessment

Fig. 7 shows that the reliability distribution of the Gumbel model can take different shapes. The PDF in Fig. 7(a**)** is skewed to the left and thus depicts negative skewness, in which the left tail is elongated. The Gumbel distribution governs the load as a measurement of the duration in failure processes. The estimation of the scale parameter β is based on the Gumbel distribution characterisation.

Rural **Urban**



(a)



(b)

Fig. 7 (a) PDF and (b) CDF for both roads.

Some of the specific characteristics of the Gumbel distribution that relate with the PDF graph in Fig. 7 are as follows [22].

i. The shape of the Gumbel distribution is skewed to the left. The PDF of this distribution has no shape parameter and has only one shape, which does not change.
ii. The PDF of the Gumbel distribution has a location parameter μ , which is equal to the

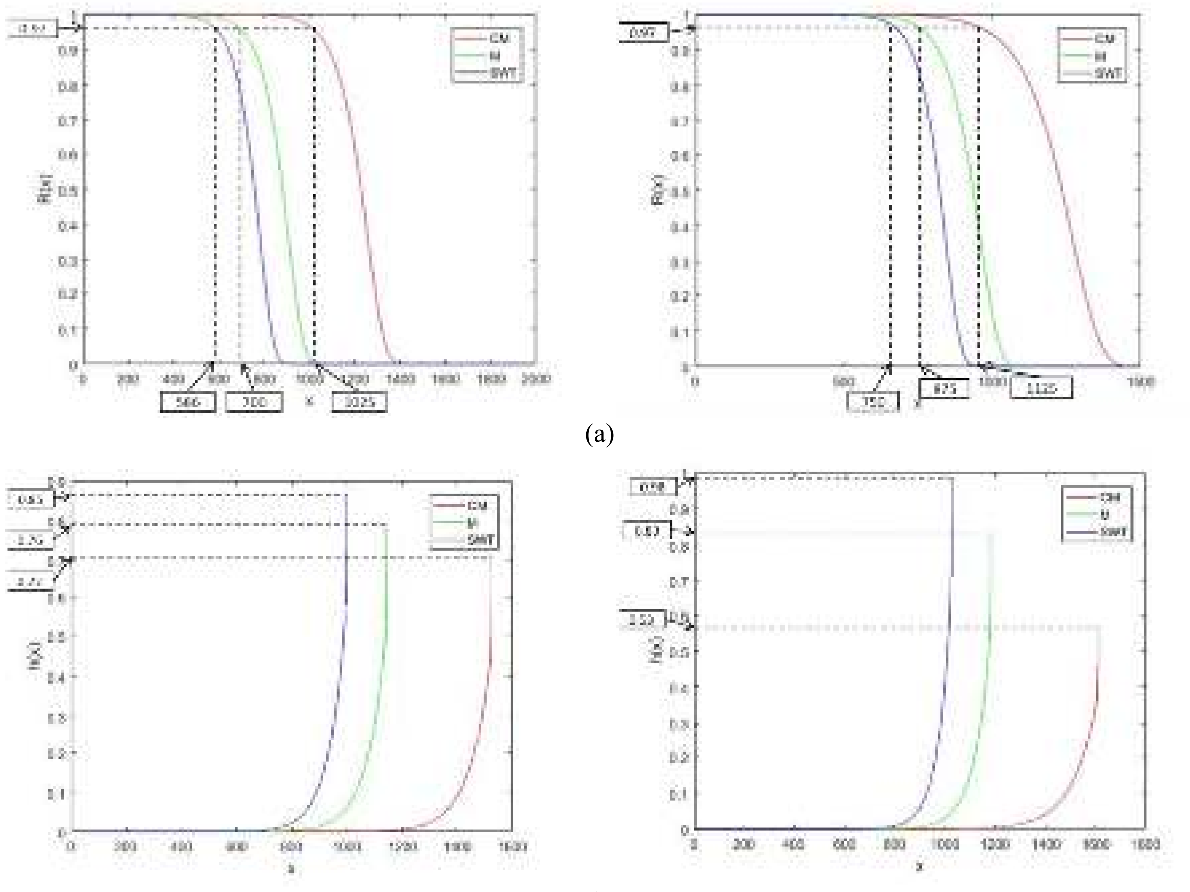
mode but differs from the median and the mean. This condition is because the Gumbel model is not symmetrical about it μ .

iii. As μ decreases, the PDF shifts to the left. As μ increases, the PDF shifts to the right.

In Fig. 8(b), the CDF accumulates the probability and shows an increasing function for both roads (rural and urban) of each fatigue life prediction model (Coffin-Manson, Morrow and SWT) from 0 to 1. The 0 values are less than the least value for the random variable and 1 for the highest value of the random variable.

The reliability function show in Fig. 9(a) that the reliability for rural 586, 700 and 1025 cycles as Coffin-Manson, Morrow and SWT respectively with proportion surviving in 0.97 (97%). While, survival for the urban road was proportion surviving for Coffin-Manson, Morrow and SWT more than 750, 875 and 1125 cycle in 0.97 (97%), same as rural road condition. Failure rate of the hazard rate function graph for rural road in Fig. 9(b) increase with time which the Coffin-Manson failure ratio at 0.72, Morrow at 0.76 and SWT 0.85 failure per unit cycle. Meanwhile, urban road condition also shows the increasing of failure ratio at 0.53, 0.83 and 0.98 failure per unit cycle for Coffin-Manson, Morrow and SWT respectively. The hazard rate function curve was nearly to the wareout life because the failure rate was increasing with time cycles.

Rural **Urban**



(a)

(b)

Fig. 8 Reliability assessment for both roads; (a) reliability function, (b) hazard rate function.

Table 3 Statistical moment comparison between risk assessment and fatigue life model

Road	Coffin-Manson		Morrow		SWT	
	β	MTTF (cycle)	β	MTTF (cycle)	β	MTTF (cycle)
Rural	75	1.25×10^3	66	9.05×10^2	61	7.79×10^2
Urban	94	1.27×10^3	62	9.58×10^2	51	8.41×10^2

In prediction of desired reliability life, understanding the physics and failure mechanism of components during operation is important. The statistical moment of the original and retention signals among the fatigue damage models of the two roads is shown in Table 4. This observed that the MTTF values for two parameter of Gumbel distribution occur earlier as predicted. MTTF prediction is essential in reducing the failure rate of the components. The MTTF provides essential failure estimation, which assists in the development of maintenance schedules and manners of usage. The mean life of the component based on the number of cycles to failure is equal to life. The different values of the fatigue life prediction models (Coffin-Manson, Morrow and SWT) are caused by the mean stress within the data signal.

4. Conclusions

A signal retention technique based on time domain on correlated fatigue damage was used to remove low-amplitude signal cycles. This technique approaches the high amplitude, which produces damage that is retained in the shortened time of the new signal. They were retained from the original signal with times of 120 s to 72 and 60 s for 100% retention, and the rest of the retention percentages (95% to 85%) were retained between 15 and 7.4 s. The original and retained signals produced the statistical parameters of mean, kurtosis, skewness, standard deviation and variance values. The retention signal helped improve the life and extraction but did not affect the content and behaviour between the original and retention signals because it only removed the minimum fatigue damage potential. The total damage for the original signal of the rural road and 100% retention was the same at 9.16×10^{-4}, 1.32×10^{-3} and 1.57×10^{-3} for Coffin-Manson, Morrow and SWT, respectively. The same was observed for the total damage for the urban road between the original and 100%, 9.04×10^{-4}, 1.19×10^{-3} and 1.36×10^{-3} for Coffin-Manson, Morrow and SWT, respectively.

For life prediction component in reliability, Gumbel distribution was used to evaluate the scale parameter of different fatigue life prediction models. The different pattern parameters and MTTF were relevant in the contexts of failure replacement and component aging. The scale parameter showed that the component underwent positive aging, which indicated that the wear condition decreased to increasing failure over time component; the rural failure ratios were 0.72, 0.76 and 0.85 and those for the urban road were 0.53, 0.83 and 0.98 under Coffin-Manson, Morrow and SWT, respectively.

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