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Wavelet-based Bumps Identification in Strain Time Histories for Accelerated Durability Analysis

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ABSTRACT

This study focuses on characterising the wavelet coefficients in the strain time histories of coil springs to extract bump signals that have contributed to high fatigue damage for accelerated durability analysis. Durability analysis in the time domain is commonly associated with long loading signals, which require high computational time. Through identifying high-amplitude cycles or bumps, the signal length can be reduced while still maintaining the fatigue properties. This method is commonly known as fatigue data editing (FDE). The methodology started by extracting the high wavelet energy segments in the time loading histories using the continuous wavelet transform (CWT). Analysis findings revealed that the high magnitude wavelet coefficient is highly correlated with high amplitude cycles or bumps. The efficiency of FDE to reduce the strain signal length was controlled by the gate value selected. For the resident road signal, the appropriate gate value was found to be 70% of the maximum wavelet coefficient magnitude, which gave 93.44% of signal length reduction while preserving the original fatigue damage. Meanwhile, a signal reduction of 78.23% was reported in the highway signal at a gate value of 50%. This showed that isolating the high magnitudes in the CWT wavelet coefficients can effectively extract the bump events that contributed to high fatigue damage. Hence, CWT is proven to be an appropriate technique for identifying damaging segments in random strain histories and achieving optimised signal length reduction for accelerated durability analysis.

INTRODUCTION

Vehicle passengers experience vibration when the vehicle travels over a road with an uneven surface. This vibration arises from the excitation caused by the road surface through the tyres and suspension system (Chin et al., 2022). Potholes and bumps cause large-amplitude shocks as the car moves over them. Vibrations generated by road irregularities like bumps and potholes can greatly alter the wheel movement

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and passenger comfort. Therefore, a suspension system is essential to absorb vibration energy, ensuring safety, driving stability, and ride comfort. Long-term random cyclic loading from the road surface leads to fatigue failure in suspension components, especially in the coil spring and lower suspension arm, as these parts bear most of the vibration (Bergh et al., 2021; Chin et al., 2025; Yuan-Chun, 2019). Hence, vehicle components must undergo durability testing to meet the standards of safety, reliability, durability, and comfort.

The durability of an engineering component is highly relied on its geometric design, the material's fatigue properties, and its loading history. To minimise failures, fluctuating service loads are assessed using the safe-life approach (S–N or ε–N) in durability prediction for automotive components (Chin et al., 2024). Using strain gauges and accelerometers, the time-domain approach enables the characterization of operational loading conditions and is extensively employed in the evaluation of component durability. In comparison with conventional strain–life models, Chin et al. (2021b) revealed that the effective strain damage (ESD) model exhibits enhanced capability in fatigue life predictions of automotive suspension components under variable-amplitude loading conditions. However, this method is limited by the signal time interval. A substantial volume of sample data is necessary to simulate the statistical characteristics of stochastic processes, thereby increasing the computational cost of the analysis (Liu et al., 2022; Ugras et al., 2019). Hence, fatigue data editing (FDE) approaches have been introduced to shorten signal length and speed up durability analysis.

FDE is commonly used to reduce the input signal length without altering its original characteristics (Mohseni et al., 2022; Yang et al., 2023). The loading histories in many engineering applications usually contain both high- and low-amplitude cycles. High-amplitude cycles cause most of the fatigue damage, while low-amplitude cycles contribute very little (Putra et al., 2020). Therefore, removing low-amplitude or low-damage segments is appropriate, provided the total fatigue damage remains unchanged. This reduction in data allows faster durability analysis. Recent studies have used the continuous wavelet transform (CWT) to support FDE in analysing loading histories. In the automotive field, Mattetti et al. (2012, 2015) applied an FDE technique that reduced tractor fatigue testing time from 4100 hours to 601 hours. Similarly, Putra et al. (2020) used CWT in FDE to shorten signal length by more than 33%, while preserving over 90% of the original fatigue damage for suspension coil spring loading histories.

This study aims to identify and extract high-damage bump signals from suspension coil spring loading histories using wavelet energy for FDE applications. A major drawback of current FDE techniques is the inconsistency in signal-length reduction, which depends on signal behaviour. This variability results from the random and non-stationary nature of road-induced loading histories. Bump events in random signals often appear as sudden amplitude changes, known as singularities, which contribute significantly to fatigue damage. Hence, singularities in loading history signals can be used for FDE, as a high number of singularities generally indicates higher fatigue damage. It is hypothesised that singularities in time histories can be extracted using CWT to identify damaging segments within the signal.

THEORETICAL DEVELOPMENT OF SIGNAL PROCESSING AND FATIGUE LIFE ASSESSMENT

Signal processing in frequency domain

Time-domain analysis of strain histories in vehicle suspension systems does not provide information about their frequency characteristics. The Fourier Transform (FT) had been commonly applied to evaluate the frequency data of a time series, allowing identification of all frequency components within a signal. The Fast Fourier Transform (FFT) has been widely utilised as an efficient technique for converting time-series data into its corresponding frequency spectrum. The Fourier Transform, represented as $\hat{f}(\omega)$, is

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mathematically defined as the scalar product of the time-domain signal $f(t)$ and the complex exponential function $e^{j\omega t}$ (Kunpeng et al., 2009):

$$\hat{f}(\omega) = \int_{-\infty}^{\infty} f(t)\, e^{-j\omega t} dt \tag{1}$$

Frequency-domain analysis can be carried out using the Power Spectral Density (PSD), as expressed in Equation 2:

$$\int_{-\infty}^{\infty} S_x(f) df = \int_{-\infty}^{\infty} \lim_{T\to\infty} \frac{|x(f)|^2}{T} df = \lim_{T\to\infty} \int_{0}^{T} \frac{x^2(t)}{T} dt \tag{2}$$

where $x(t)$ represents the random signal in the time domain, $x(f)$ denotes the amplitude of the frequency spectrum, and $S_x(f)$ refers to its power spectral density. The PSD quantifies the energy content of a signal, which corresponds to the area under its curve. This is particularly valuable in durability analysis, as the signal's energy content is directly linked to fatigue damage. A higher energy level in the signal indicates greater fatigue damage.

Continuous wavelet transform (CWT) for time-frequency analysis

The Continuous Wavelet Transform (CWT) is adopted to overcome the resolution constraints inherent in the Short-Time Fourier Transform (Zhou et al., 2025). CWT applies a variable-size window function, which is larger at lower frequencies and smaller at higher frequencies. In contrast to the Fourier Transform, which assumes a time function as a combination of sinusoidal components with varying frequencies and phases, CWT breaks the signal into small mother wavelet functions $\psi_{(s,u)}(t)$ with different shift and scale information, as illustrated below (Shi et al., 2025):

$$\psi_{s,u}(t) = \frac{1}{\sqrt{s}} \psi\left(\frac{t-u}{s}\right) \tag{3}$$

where *s* and *u* represent the scaling and translation parameters, respectively. The mother wavelet function must comply with the admission conditions below:

$$\int_{-\infty}^{\infty} \psi(t)\, dt = 0, \int_{-\infty}^{\infty} \psi^2(t)\, dt = 1 \tag{4}$$

When the conditions in Equation 4 are satisfied, the CWT of a signal $f(t)$ is then defined as:

$$W_{\psi} f(s,u) = \langle f(t), \psi_{s,u}(t) \rangle = \frac{1}{\sqrt{s}} \int_{-\infty}^{\infty} f(t) \psi^*\left(\frac{t-u}{s}\right) dt \tag{5}$$

The CWT and complex-valued wavelets are effective in detecting transients and singularities within signals (Li & Chen, 2014). Therefore, load histories of vehicle suspensions that contain transient events are best analysed using CWT. Moreover, CWT is advantageous in fatigue data editing (FDE) because it employs smaller windows at higher frequencies and can detect small amplitude variations more effectively than fixed-window methods (Putra et al., 2017).

Durability assessment

To initiate a durability analysis, knowledge of component geometry, fatigue mechanical properties, and service loads is required. Durability assessment entails identifying fatigue cycles within the loading history and subsequently determining the cumulative damage (Zorman et al., 2021). The Rainflow counting

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algorithm enables the extraction of fatigue cycles from loading time histories. Originally proposed by Matsuishi and Endo in 1968, this algorithm has become a standard technique for evaluating service loading conditions owing to its proven reliability in durability analysis (Marsh et al., 2016; Paraforos et al., 2014). It converts the time loading signals into peaks and valleys series that represent the local maxima and minima of the signal, corresponding to the load reversals. A complete fatigue cycle can be explained as the stress range between two points enclosed by adjacent peaks of higher and lower magnitudes.

In durability analysis, the stress–life and strain–life methods are commonly applied in industry practices to calculate the number of cycles to failure (N_f). The stress–life method offers satisfactory accuracy within the high-cycle fatigue region ($N_f > 10^3$), whereas the strain–life method incorporates the influence of plastic strain, making it more applicable to the low-cycle fatigue domain ($N_f \leq 10^3$). The strain–life relationship, derived as an extension of the stress–life concept, is expressed as follows:

$$\Delta\sigma = \frac{E \cdot \varepsilon_e}{2} = \sigma_f^{'} \cdot (2N)^b \tag{6}$$

where ε_e represents the elastic strain, N is the number of cycles to failure, $2N$ denotes the total number of load reversals to failure, σ_f' is the fatigue strength coefficient, and b is the fatigue strength exponent (typically negative). In addition, the plastic strain component ε_p is expressed as follows:

$$\frac{\varepsilon_p}{2} = \varepsilon_f^{'} \cdot (2N)^c \tag{7}$$

where ε_f' denotes the fatigue ductility coefficient, and $c$represents the fatigue ductility exponent. The total strain amplitude is determined by the summation of its elastic and plastic components. By integrating Equations 6 and 7, the overall strain amplitude can thus be formulated:

$$\varepsilon_T = \varepsilon_e + \varepsilon_p = \frac{\sigma_f^{'}}{E} \cdot (2N)^b + \varepsilon_f^{'} \cdot (2N)^c \tag{8}$$

Morrow's model accounts for the influence of mean normal stress by modifying the strain–life relationship through the inclusion of the mean stress σ_m. The model suggests replacing σ_f' with $\sigma_f' - \sigma_m$ to incorporate the mean stress effect, as expressed in Equation 9:

$$\frac{\Delta\varepsilon}{2} = \frac{(\sigma_f^{'} - \sigma_m)(2N)^b}{E} + \varepsilon_f^{'} \cdot (2N)^c \tag{9}$$

Here, σ_m is considered positive under tensile loading and negative under compressive loading. Smith, Watson, and Topper (SWT) introduced an alternative formulation derived from strain–life fatigue test data obtained at fracture under various mean stress conditions, as presented in Equation 10:

$$\sigma_{max}\varepsilon_a = \frac{\left(\sigma_f'\right)^2}{E}\left(2N_f\right)^{2b} + \sigma_f'\varepsilon_f'.\left(2N_f\right)^{b+c} \tag{10}$$

where σ_{max} is the maximum stress and ε_a is the alternating strain.

The Palmgren–Miner linear damage rule was independently proposed by A. Palmgren (1924) and M. A. Miner (1945), as cited by Ghafoori et al. (2015). It is extensively utilised to estimate the cumulative fatigue damage in components exposed to loading with varying amplitudes. When integrated with the Rainflow cycle counting method, the rule provides consistent and reliable results. The Palmgren–Miner

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rule assumes that the total fatigue damage is determined by summing the damage contributions from all individual cycles, such that:

$$D = \sum \left(\frac{n_i}{N_f} \right) \tag{11}$$

where N_f represents the number of cycles to failure, and n_i denotes the number of applied cycles. The accumulated damage, D, ranges from zero, corresponding to an undamaged component, to one, indicating complete fracture.

METHODOLOGY

Fig 1 illustrates the overall methodological process flow. Strain time histories were measured from the coil spring through road testing on different roads. The recorded signals were subsequently analysed using various signal processing techniques encompassing both frequency-domain and time-frequency-domain approaches. Using the techniques, the singularities, representing bump events, were identified and isolated. The extracted singularities were then used in Fatigue Data Editing (FDE), where they were recomposed into a signal with reduced length. Finally, fatigue damage calculation was carried out from the reduced signals, which must not lose more than 10% of the fatigue damage information.

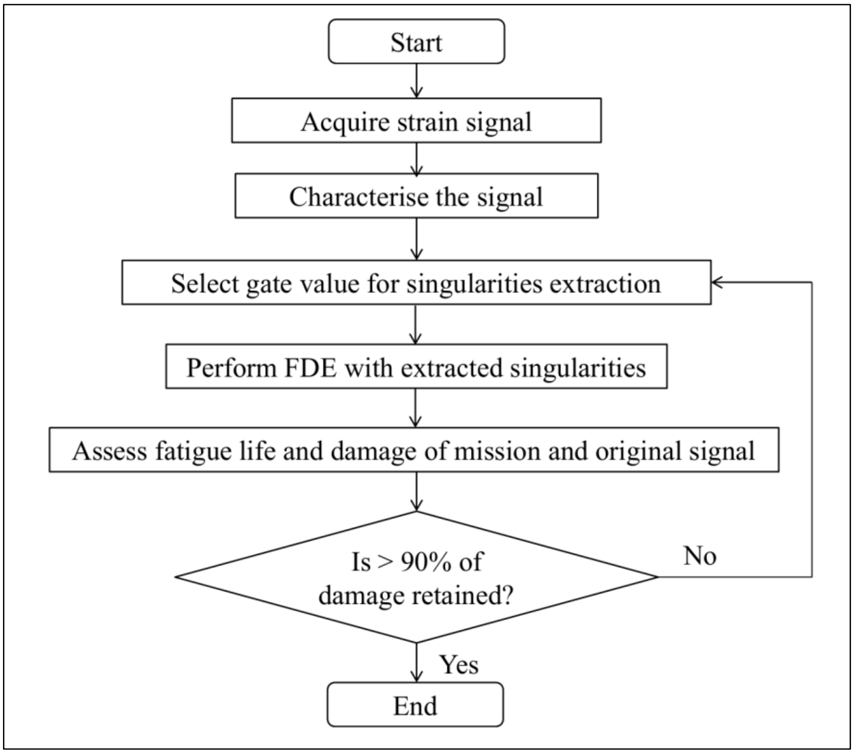

Fig. 1. Process flow of singularities extraction and FDE.

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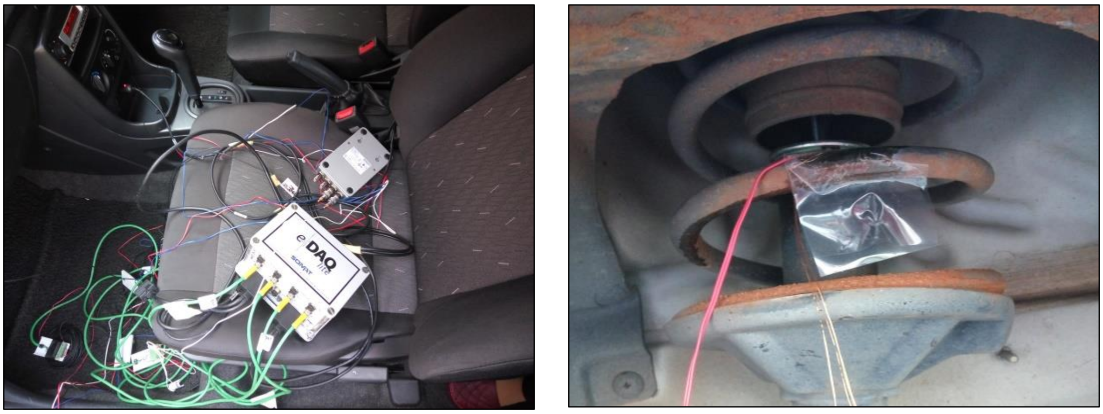
Strain data measurement via road tests

Via on-road testing, the strain data were obtained from the suspension coil spring, during which strain responses were measured while the vehicle was in operation. The tested car was a Malaysian-manufactured 1300 cc sedan with a passive MacPherson suspension system. The coil spring has a stiffness of 16,806 N/m with a mean diameter of 130 mm and 6 active coils. As illustrated in Fig 2, a SoMAT eDAQ data acquisition system, coupled with a strain gauge, was employed to capture the strain signals. A Kyowa uniaxial strain gauge with 2mm gauge length (Model: KFGS-2-120-C1-11 L3M2R) was utilised. The strain gauge was securely affixed to the surface of the coil spring to ensure accurate measurement. To maintain signal fidelity, the sampling frequency was required to exceed 400 Hz; thus, 500 Hz was set as the sampling rate in the data acquisition to prevent significant loading information loss (Chin et al., 2025). Two distinct road conditions, residential and highway, were investigated, as shown in Fig 3, with strain data recorded for a total duration of 80 seconds for each condition.



(a) (b)

Fig. 2. Strain signal measurement: (a) data acquisition instruments and (b) strain gauge.

(a) (b)

Fig. 3. Tested road conditions: (a) resident area and (b) highway.

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Signal characterisation

In this study, the strain histories obtained from road tests were examined with the Power Spectral Density (PSD) and CWT analysis. Through the Fast Fourier Transform (FFT), the recorded strain signals were converted into a frequency spectrum to identify the dominant frequency components. The PSD was subsequently computed to determine the power energy distribution across various frequency ranges. To further investigate the temporal evolution of frequency content, the Continuous Wavelet Transform (CWT) was employed. The Morlet wavelet was chosen for CWT analysis. Wavelet coefficients were extracted from the strain signals using the CWT, as defined in Equation 5, and represented in the time–frequency plane to visualise the variation of signal characteristics with respect to both time and frequency.

Identify bumps events via singularities and FDE

Since the CWT reveals the time–frequency properties of a signal, it enables the detection of discontinuities through variations in the wavelet coefficients. Transient events or singularities within a signal typically cause abrupt changes in the structural response, which are reflected by significant amplitude variations (Zhang et al., 2016). Therefore, the identification of transients or singularities was based on the magnitude of the wavelet coefficients. A threshold, or gate value, was established to distinguish high-amplitude cycles (associated with singularities) from low-amplitude cycles. Cycles with coefficient magnitudes below the gate value were removed, while those above the threshold were retained. In this study, several gate values ranging from 30% to 80% of the maximum coefficient magnitude were tested to determine the most appropriate threshold. The gate value was defined as follows:

$$GateValue = n \times \left|W_{\psi}f(s,u)\right|_{max} \tag{12}$$

where n represents the percentage of the maximum coefficient magnitude, ranging from 30% to 80%. The retained wavelet coefficients were reversed into time series using the inverse Continuous Wavelet Transform (inverse-CWT) to determine the time locations of the singularities or bump events. Next, bump events were then isolated from the original signal according to their identified time positions and compiled to form the mission signal.

Fatigue life assessment

Table 1 provides the mechanical and fatigue properties of the coil spring's material, SAE5160 carbon steel. In this study, the strain–life approach was used, since automotive suspension coil springs are often exposed to severe loading conditions that might induce plastic strain. A finite element analysis of a coil spring, conducted in a previous study (Chin et al., 2021a), indicated a maximum von Mises stress of 1136 MPa under a static load of 3600 N, which was 76% of the material's yield strength. This suggested that although the coil springs are mostly operating within the elastic region, plastic strain is also possible under extreme overloads, especially during bump events. Thus, strain-life approaches were chosen to take both elastic and plastic strains into account for the calculation of fatigue life. Fatigue lives corresponding to both the original strain signals and the frequency-localised signals within various frequency bands were estimated using established strain–life models, namely the Coffin–Manson, Smith–Watson–Topper (SWT), and Morrow formulations. The fatigue damage associated with the reconstructed signals was subsequently benchmarked with that of the pre-processing data to evaluate the level of fatigue damage preservation. From a practical standpoint, a FDE algorithm should be able to retain fatigue damage higher than 90% of the original data, as most of the low-amplitude cycles contribute negligibly to overall fatigue damage. If the retained damage differs by more than 10% from the original, the bumps extraction procedure should be repeated using a lower gate threshold to enhance the proportion of preserved damage.

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RESULTS AND DISCUSSION

Loading histories characteristics

The strain loading histories were obtained in this study under two different road conditions: highway and residential area. The corresponding time histories for both conditions are presented in Fig 4. It was observed that the strain amplitude range for the residential area road was significantly larger than that of the highway. This is due to the uneven surface characteristics of residential roads, which often include features such as speed bumps and minor surface irregularities. In contrast, highways are typically well-maintained to ensure a smooth surface profile for driving safety, resulting in strain signals with relatively small amplitude variations.

Table 1. Mechanical and fatigue properties of SAE5160 carbon steel

Properties	Value
Modulus of elasticity, E (GPa)	207
Shear modulus, G (GPa)	80 (for typical steel)
Yield strength (MPa)	1487
Fatigue strength coefficient, σ_f' (MPa)	2063
Fatigue strength exponent, b	-0.08
Fatigue ductility coefficient, ε_f'	9.56
Fatigue ductility exponent, c	-1.05

Furthermore, distinct singularities corresponding to sudden and large changes in strain amplitude were evident in the residential area signal. These singularities, labelled S1–S7, occurred at time positions 4 s, 16 s, 31 s, 42 s, 51 s, 60 s, and 71 s, as shown in Fig 4(a). Among them, singularity S4 exhibited the highest strain amplitude change of 709 με. Such abrupt amplitude fluctuations are attributed to the vehicle traversing speed bumps along the residential road. For the highway condition, only two singularities, which are S8 and S9, were detected, with amplitude variations of approximately 400 με, as indicated in Fig 4(b).

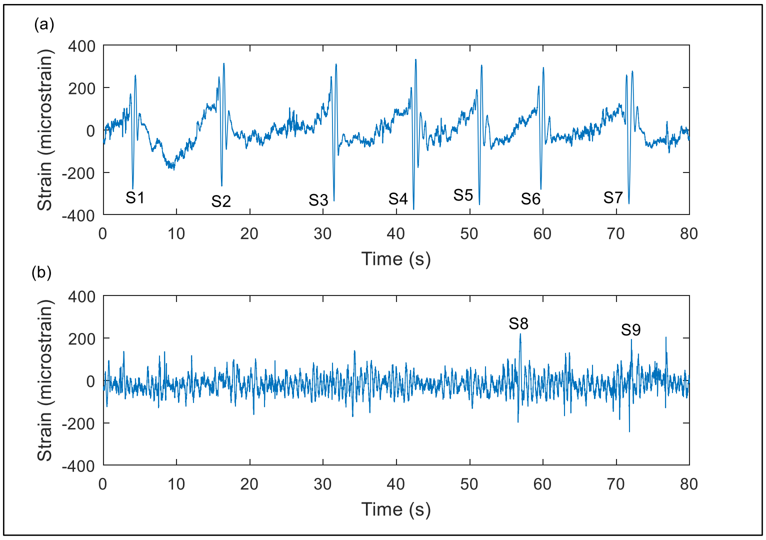

Fig. 4. Strain time histories of different roads: (a) resident area and (b) highway.

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Fig 5 presents the distribution of running fatigue damage over the time histories for both the residential area and highway conditions. As shown in the figure, regions of high fatigue damage correspond closely to the locations of the identified singularities (S1–S7). The residential area signal exhibited the highest fatigue damage of 9.19×10^{-8} at 42 s, coinciding with singularity S4, which had the largest strain amplitude variation in the time history. For the highway condition, the maximum fatigue damage recorded was 4.49×10^{-8}, aligning with the time positions of singularities S8 and S9. These findings indicate that large amplitude changes are strongly associated with significant fatigue damage. Therefore, extracting singularities corresponding to pronounced amplitude variations is crucial for accurately identifying the most damaging segments in strain signals.

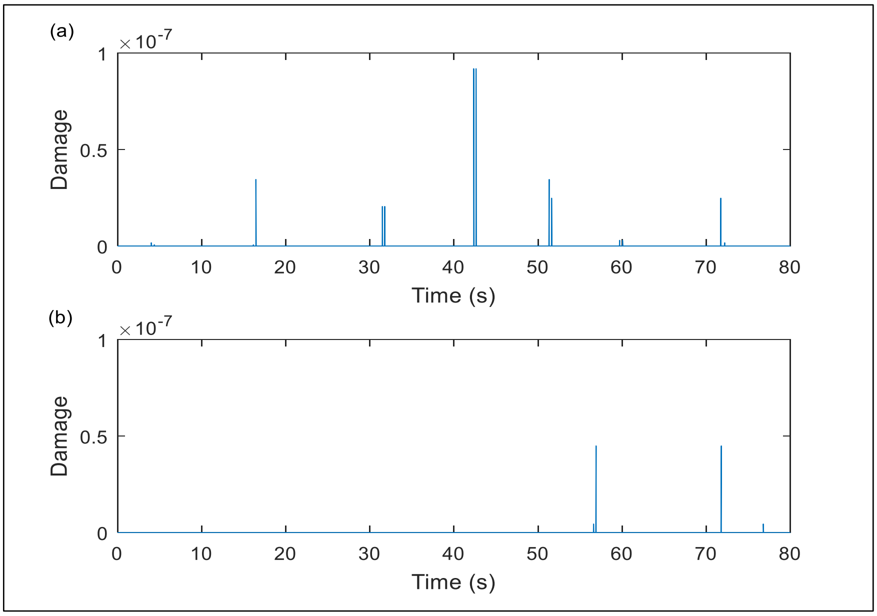

Fig. 5. Running fatigue damage in time histories: (a) resident area and (b) highway.

Frequency domain analysis

Fig 6 illustrates the PSDs of the strain signals obtained from residential area and highway conditions. Results indicate that both signals exhibited high-amplitude components primarily within the low-frequency range of 0 Hz to 10 Hz, suggesting that the fatigue events in the coil spring predominantly occurred at low frequencies. The residential area signal demonstrated a higher spectral power, reaching up to $3400\ \mu\varepsilon^2/\text{Hz}$, compared to $1050\ \mu\varepsilon^2/\text{Hz}$ for the highway signal. This finding reflects the greater energy content in the residential area signal, attributed to the increased excitation of the suspension system caused by the uneven surface conditions, such as bumps and irregularities. The total energy content of each signal, quantified as the area under the PSD curve, was calculated to be $4.497 \times 10^3\ \mu\varepsilon^2$ for the residential area and $1.803 \times 10^3\ \mu\varepsilon^2$ for the highway. The energy content of a signal is directly correlated with its potential to cause fatigue damage. Hence, signals with higher energy content are theoretically expected to induce greater fatigue damage.

Wavelet analysis

The time–frequency characteristics of both the residential area and highway strain signals were analysed using the Continuous Wavelet Transform (CWT). Fig 7 presents the corresponding time–

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frequency mappings of these signals. In the plots, the x-axis represents time, while the y-axis indicates frequency. The results confirm that high-amplitude events predominantly occurred at low frequencies, between 1 Hz and 4 Hz, for both signals. This observation is consistent with the PSD results, which showed that significant amplitude events were concentrated within the 0 Hz to 10 Hz frequency range. Additionally, the time–frequency analysis verified that the high-frequency responses observed in the highway signal (between 64 Hz and 128 Hz) did not correspond to high-amplitude or fatigue-critical events.

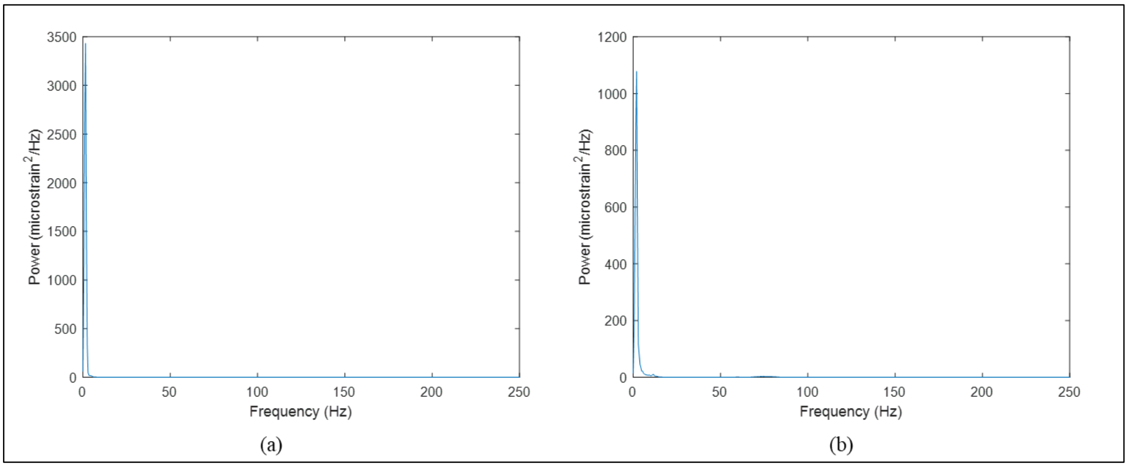

Fig. 6. PSD of strain signals of different road conditions: (a) resident area and (b) highway.

The wavelet coefficients derived from the CWT represent the energy distribution of the strain signal across the time–frequency domain. High wavelet coefficient magnitudes indicate regions of elevated energy, which are typically associated with greater fatigue damage. This correlation was validated by the alignment between the locations of high-magnitude regions in the time–frequency map and the zones of elevated fatigue damage shown in Fig 5, which also corresponded to the singularities with large amplitude changes observed in Fig 4.

These results demonstrate that wavelet coefficients serve as an effective selection criterion for identifying singularities in the Fatigue Data Editing (FDE) process. The primary advantage of using wavelet coefficients lies in their dual capability: they simultaneously indicate the temporal positions of singularities (via discontinuities) and the corresponding energy levels that reflect fatigue damage severity. As noted by Putra et al. (2020). This approach enables precise identification of damaging segments, while Pratumnopharat et al. (2014) further highlighted that wavelet-based FDE techniques can produce significantly shorter edited signals with high accuracy in retained fatigue damage.

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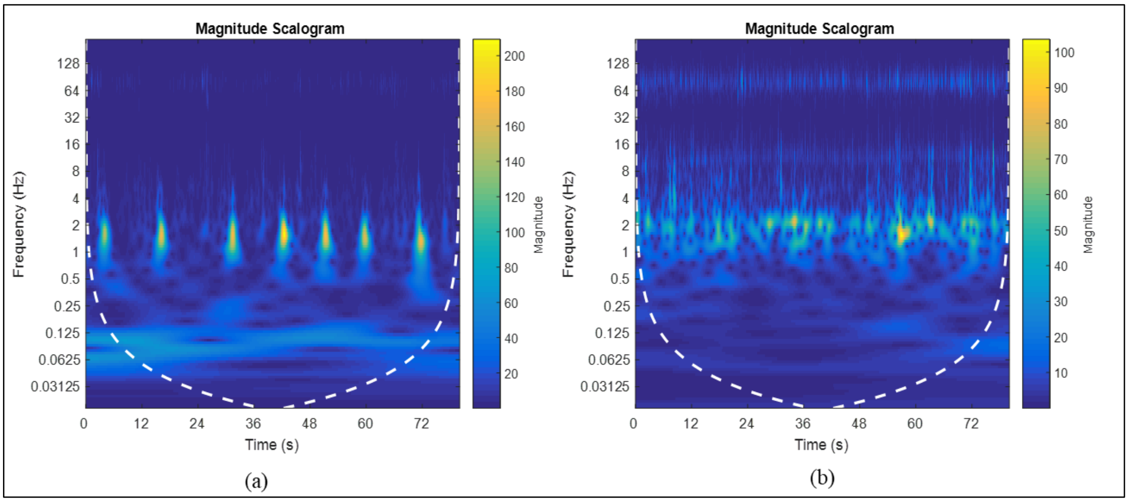

Fig. 7. Time-frequency mapping of signals by Morlet wavelet transform: (a) resident area and (b) highway.

Singularities extraction for bumps identification and FDE

To extract singularities from the original strain signals, the wavelet coefficients were filtered using various gate values. Coefficients with magnitudes lower than the selected gate value were discarded, while those exceeding the threshold were retained. For the residential area signal, gate values of 50%, 60%, 70%, and 80% of the maximum coefficient magnitude were applied. In contrast, the highway signal was filtered using gate values of 30%, 40%, 50%, and 60%. The variation in gate value ranges between the two signals is associated with their respective kurtosis values. The residential area signal exhibited a kurtosis of 5.67, whereas the highway signal recorded a lower kurtosis of 4.77. The higher kurtosis in the residential area signal indicates the presence of more extreme values in the strain dataset, reflecting a greater number of transient events or singularities with large amplitude deviations from the mean. This was consistent with the fatigue damage distribution shown in Fig 5(a), where singularities accounted for most of the total fatigue damage. Although low-amplitude cycles also contribute to fatigue damage, their impact is relatively minor. Therefore, higher gate values were necessary for the residential area signal to ensure that only the dominant, damage-inducing singularities associated with high coefficient magnitudes were extracted. This approach prevented the inclusion of low-amplitude cycles that produced negligible damage.

Conversely, the lower kurtosis value in the highway signal suggests fewer extreme values and a more uniform strain distribution. As a result, a significant portion of fatigue damage in the highway condition originated from lower-amplitude cycles. To capture these cycles effectively, a lower gate value range was selected for the highway signal. The extracted singularities for the residential area and highway signals at different gate values are illustrated in Figs 8 and 9, respectively. These extracted singularities were then reconstructed into mission signals of shorter duration, as shown in Figs 10 and 11.

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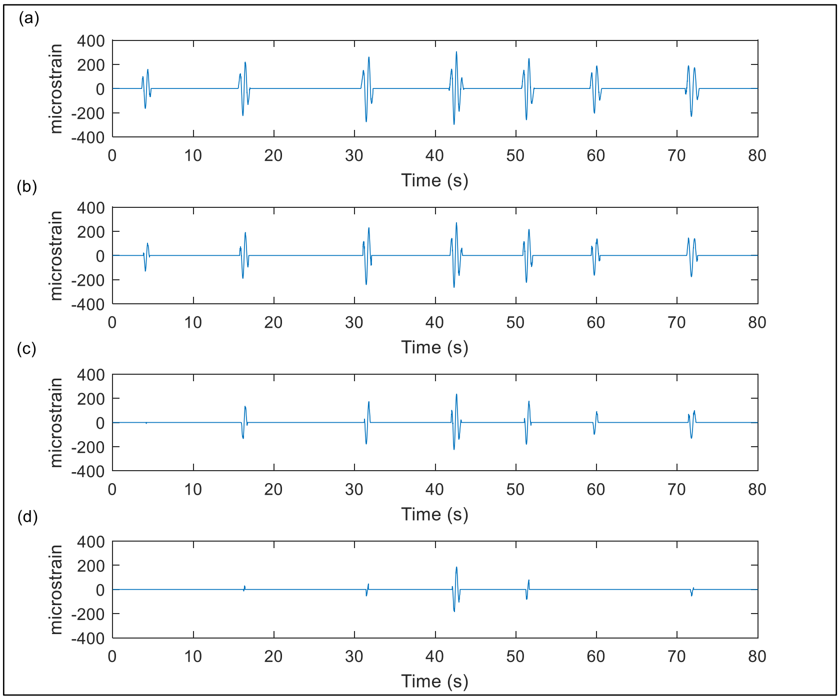

Fig. 8. Extracted singularities from resident area signal at gate value of (a) 50%, (b) 60%, (c) 70%, and (d) 80% of maximum coefficient magnitude.

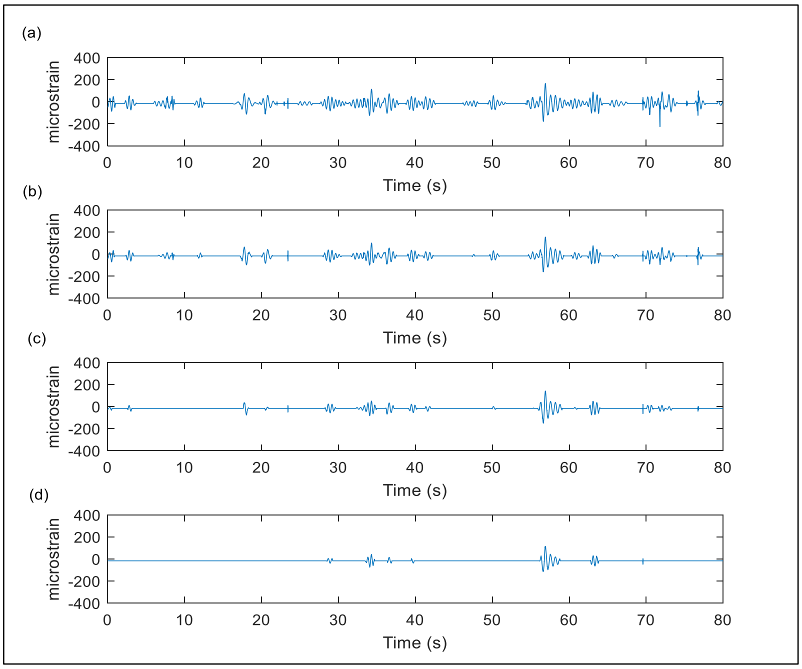

Fig. 9. Extracted singularities from highway signal at gate value of (a) 30%, (b) 40%, (c) 50%, and (d) 60% of maximum coefficient magnitude.

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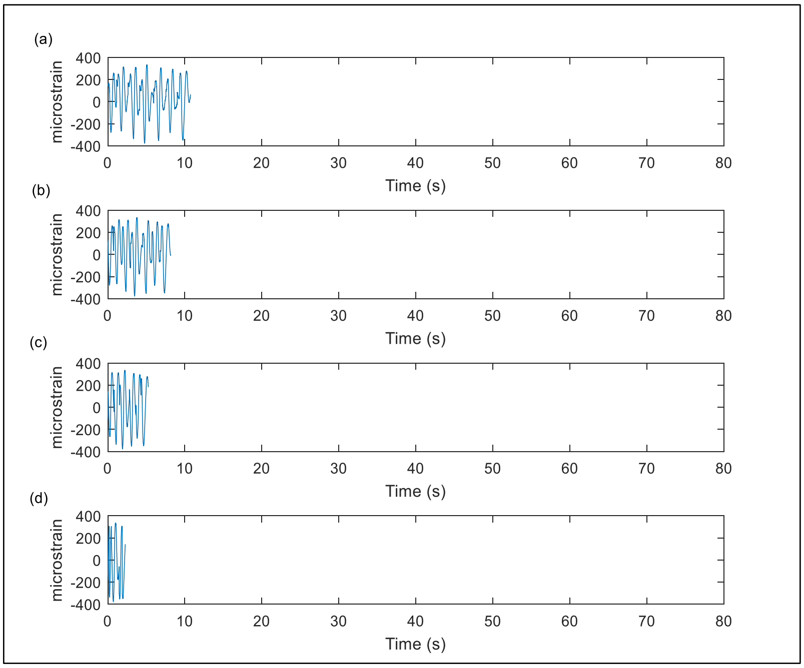

Fig. 10. Mission signals of resident area composed of extracted singularities at gate value of (a) 50%, (b) 60%, (c) 70%, and (d) 80% of maximum coefficient magnitude.

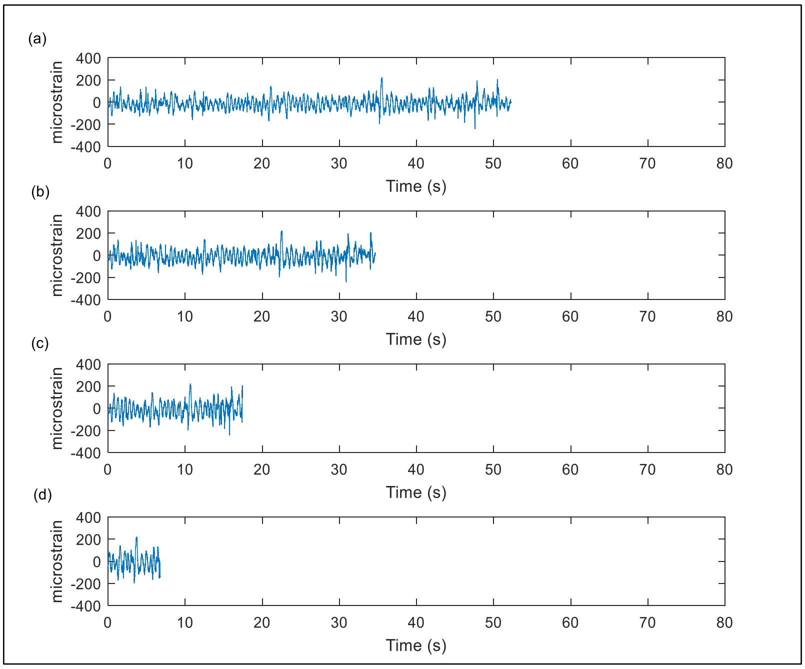

Fig. 11. Mission signals of highway composed of extracted singularities at gate value of (a) 30% (b) 40% (c) 50% (d) 60% of maximum coefficient magnitude.

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Fatigue damage assessment

The total fatigue damage of the original strain signals under both road conditions was quantified using strain–life relationships, as illustrated in Fig 12. The total fatigue damage is the accumulation from the fatigue damage contributed by each fatigue cycle in the loading blocks. The findings revealed that the signal corresponding to the residential area exhibited substantially higher fatigue damage than that of the highway, aligning with the Power Spectral Density (PSD) analysis shown in Fig 6. This behaviour can be attributed to the higher energy content induced by the rougher and more irregular surface of the residential road. Subsequently, the fatigue damage of the edited signals was compared with that of the original data to evaluate the percentage of damage retention. Table 2 summarises the results of damage retention and signal length reduction across different gate values. It was found that increasing the gate threshold resulted in a more pronounced reduction in signal length due to the removal of low-amplitude cycles; however, this also led to a decline in retained damage, as excessive cycle elimination may exclude segments contributing to fatigue. Hence, determining an optimal gate value in the FDE process is essential to achieve a balance between data compression and damage preservation, ideally ensuring that at least 90% of the original damage is retained while minimising the overall signal length.

For the residential area signal, the optimal gate value was determined to be 70% of the maximum wavelet coefficient magnitude. At this level, the signal length was reduced from 80 s to 5.248 s (a 93.44% reduction), while still retaining 99% of the original fatigue damage. For the highway signal, the most suitable gate value was 50%, which achieved a signal length reduction of 78.23% and nearly 100% damage retention. These findings demonstrate that singularity-based extraction is highly effective for isolating the damage-inducing segments in load histories, as the edited signals preserved almost all of the original fatigue damage. The analysis also provided insights into the influence of low-amplitude cycles on overall fatigue damage (Gates & Fatemi, 2018). In the residential area signal, the retained fatigue damage showed only a slight decrease as the gate value increased from 70% to 80%, indicating that low-amplitude cycles contributed minimally to total fatigue damage. Thus, their removal had little impact on damage retention. Conversely, in the highway signal, damage retention dropped sharply—from approximately 100% to about 30%—when the gate value increased from 50% to 60%. This suggests that a significant proportion of fatigue damage in the highway condition originated from cycles with coefficient magnitudes between 50% and 60% of the maximum value. Eliminating these cycles at higher gate values caused a substantial reduction in retained damage.

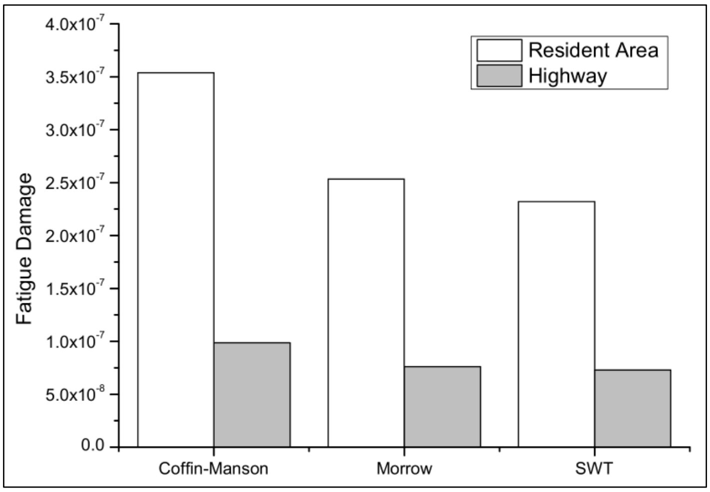

Fig. 12. Total fatigue damage calculated from the loading strain histories in resident area and highway using Coffin-Manson, Morrow and SWT strain-life models.

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Table 2. Damage retention and signal length reduction in mission signals after FDE

Road condition	Wavelet coefficient gate value (%)	Damage retained (%)			Signal length reduction (%)
		Coffin-Manson	Morrow	SWT	
Resident Area	50	100.00	100.00	99.93	86.58
	60	100.00	100.00	99.91	89.80
	70	99.30	99.20	99.08	93.44
	80	91.55	87.91	86.42	97.18
Highway	30	100.00	100.00	100.00	34.71
	40	100.00	100.00	100.00	56.70
	50	100.00	100.00	99.98	78.23
	60	17.11	30.89	35.48	91.64

CONCLUSION

In this study, the CWT was utilised for the detection and extraction of singularities, representing bump-induced events, in the loading histories of a coil spring. Via CWT, these singularities, which are closely correlated with high fatigue damage, appeared as high magnitude wavelet coefficients at specific time and frequency. Subsequently, FDE was performed on the strain loading signals collected from different road conditions by isolating the high magnitude wavelet coefficients and extracting the singularities. The results confirmed that CWT is an effective technique for identifying singularities, as it can sensitively capture variations in strain amplitude, particularly at higher frequencies. The wavelet-based FDE approach demonstrated excellent performance in reducing the signal length whilst preserving the fatigue properties in the original loading signals. For the residential area signal, a signal length reduction by 93.44% was reported without significantly changing the original fatigue damage. In the case of the highway signal, 78.23% of the signal length was removed while maintaining nearly 100% of the original fatigue damage. These outcomes strongly support the wavelet-based FDE method as a highly efficient tool for compressing loading histories without altering the original fatigue characteristics. The findings successfully validate the hypothesis proposed in this study.

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CONFLICT OF INTEREST STATEMENT

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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AUTHORS' CONTRIBUTIONS

The authors confirm their contribution to the paper as follows: study conception and design: C. H. Chin, S. Abdullah; data collection: C. H. Chin; analysis and interpretation of results: C. H. Chin; draft manuscript preparation: C. H. Chin, S. Abdullah, A. Jedi. All authors reviewed the results and approved the final version of the manuscript.

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