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A cyclic simulation approach for the generation of the non-stationary load histories of engineering vehicles †

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Abstract

The present paper focuses on the simulation of the non-stationary load histories of engineering vehicles for fatigue tests. For the first time, the characteristics of the service loads experienced by engineering vehicles are described. Then rainflow data-reduction contributing to reduce the testing time and extrapolation of each operating section to generate the unavailable extreme loads in a limit test are carried out. Finally, based on the simulated load history of each operating section using Markov chain Monte Carlo method (MCMC) and the corresponding simulation length generated by the Monte Carlo method, a cyclic simulation approach is proposed to generate non-stationary load histories, by which the cyclic characteristic can be reconstructed well. The results of comparison between the observed and simulated load histories show good agreement.

Keywords: Fatigue; Engineering vehicles; Simulation; Rainflow data-reduction; Extrapolation; MCMC

1. Introduction

Engineering vehicles are engineering construction machines which are used widely in the field of construction, water conservancy, electrical applications, roadwork, mining and port construction. Due to the harsh environments and bumpy roads they experience, their components are often subjected to complicated random loads which lead to frequent fatigue failures. Therefore, the accuracy of fatigue life predictions is vital to the components of engineering vehicles.

In the design stage, the Palmgren-Miner linear accumulation damage rule, the *S-N* curve relative to material performance, and rainflow cycles defined by rainflow counting algorithm are generally used for fatigue life predictions. Although this is a simple and effective method, the accuracy of the approach is quite low [1]. Further, to finally evaluate fatigue life and study the fatigue processes under stochastic load in general, it is desirable to be able to perform fatigue tests with load histories generated by simulation approaches.

The approaches found in literatures include the Markov chain Monte Carlo (MCMC) method [2, 3] and the rainflow reconstruction technique [4, 5]. The latter incorporates the auto-regressive moving average method [6]. Recently, the neural network approach [7], wavelet-based method [8, 9] and continuous model updating approach based on real-time monitoring data [10] have been proposed.

For engineering vehicles, the cyclic operation is so obvious that the service loads imposed on their components must reflect this feature. That is, the overall measured load history is non-stationary and each operating section is stationary. In other words, the non-stationary load histories consist of a sequence of stationary load sections. When simulating this sort of load histories, two issues need to be solved. First, the observed load history alternates in turn in each operating section, and the change sequence is fixed. Therefore, the generation of non-stationary load histories that reflect this alternately changing sequence needs to be addressed. Second, most simulation approaches cannot generate the extreme loads which could not be obtained in a limit test, and these extreme loads cause substantial damage of components, which has a great effect on the final determination of fatigue damage [11]. Therefore, it is desirable to extrapolate the observed load history to obtain these extreme loads before simulation.

In view of the two issues aforementioned, a simulation approach is proposed for the generation of the non-stationary load histories of engineering vehicles. The actual data is the observed load history measured at the hydraulic cylinder of a wheel loader. Primary focus is placed on the rainflow data-reduction in order to delete the small cycles that have no effect on damage accumulation. Extreme loads extrapolation is then carried out for each operating section. Further, a cyclic simulation approach is proposed in which each operating section is

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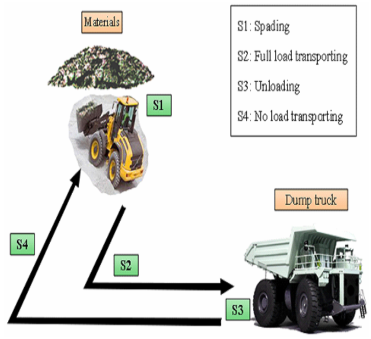
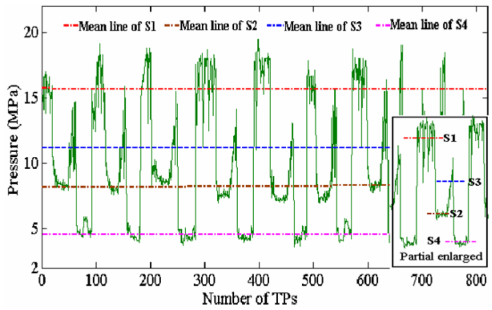


(a)



(b)

Fig. 1. (a) Cyclic operation of a wheel loader; (b) Observed load history measured at the hydraulic cylinder of a wheel loader.

simulated by MCMC simulation, and the corresponding simulation length of time variable T is generated by Monte Carlo method. Finally, a comparative analysis of the simulated and observed load histories is carried out to demonstrate the efficiency and reliability of the proposed approach. The statistical analysis and simulation have been performed with the help of the WAFO-version 2.5, a free MATLAB toolbox.

2. Characteristics of the service loads experienced by engineering vehicles

Fatigue is a major source of degradation in structural integrity of engineering structures subjected to random loads. In most case, these random loads are also non-stationary. Especially for engineering vehicles, this case is attributed mainly to the fact that they have an obvious operational feature called cyclic operation, and the changing regularity of service loads must reflect this feature.

In the current work, the wheel loader is taken as a typical example to illustrate the operational feature of engineering vehicles and the corresponding load characteristics. The wheel loader is a large engineering vehicle used primarily for loading and unloading bulk materials, and it has some fixed operating patterns such as loading and unloading, spading, leveling off, pushing the material, and traction. In practice, the V-type operating scheme is used widely in the experimental measurement of service loads [12], as exemplified in Fig. 1(a). Herein, the so-called cyclic operation mainly means that the

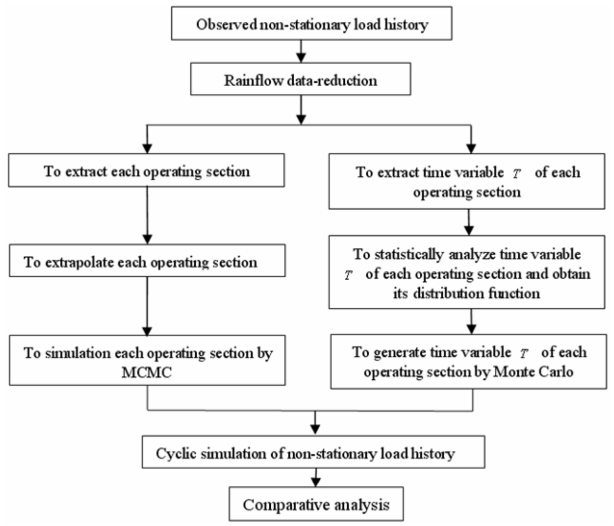


Fig. 2. Block diagram of the non-stationary load histories generation.

wheel loader works from the S1 to S4 operating sections (one operating cycle) and loops in turn [13]. As a result, as shown in Fig. 1(b), the actual measured load history obtained through the V-type operating scheme has a cyclic characteristic among each operating section as well. It is clearly seen that the whole measured load history is non-stationary and each operating section is stationary with its own mean and variance. In the following, the observed load history measured at the hydraulic cylinder of a wheel loader is used to demonstrate the validation and reliability of the proposed approach.

3. Methods

A number of probabilistic and statistical methods including rainflow data-reduction, extreme value extrapolation, MCMC simulation, and Monte Carlo method are used to generate the non-stationary load histories of engineering vehicles that reflect the cyclic characteristic among each operating section and can be used for practical experiments. The generation process can be represented schematically by a block diagram as shown in Fig. 2.

3.1 Rainflow data-reduction and extraction of each operating section

It is well known, both from practical experience and theoretical reasoning, that data-reduction in fatigue analysis is an intelligent filtering of the relevant information by removing the immense mass of data which have no effect on damage accumulation. On one hand, it is conducive to conduct fatigue life prediction and generate load history for fatigue test more conveniently and effectively. On the other hand, it is desirable that manipulations like superposition and extrapolation can be preformed directly on the reduced data-sets. After the data-reduction, we can efficiently reconstruct a load history which is useful in accelerating a test. Hence it is essential that a load

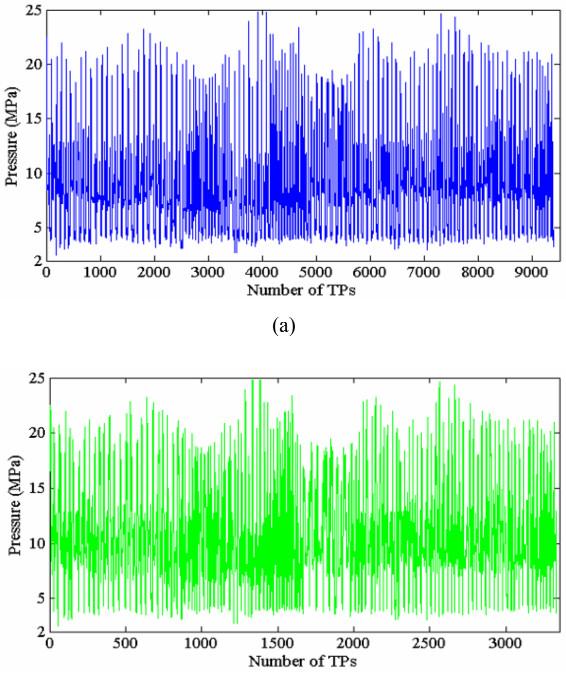


Fig. 3. Before and after graph of rainflow data-reduction: (a) observed load history measured at the hydraulic cylinder of a wheel loader with 120 operating cycles; (b) load history after rainflow data-reduction.

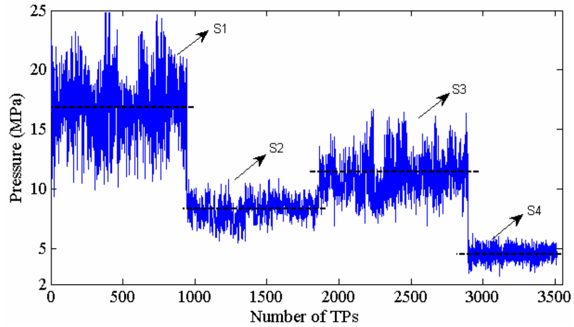


Fig. 4. Each operating section extracted from the load history after rainflow data-reduction.

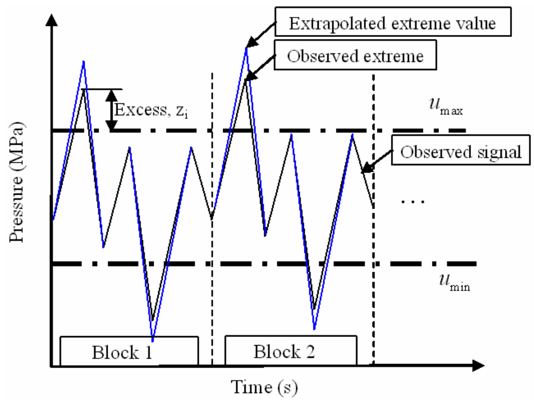


Fig. 5. Schematic diagram of POT extrapolation.

history must be data-reduced before a new random load history can be generated.

Rainflow data-reduction is an efficient method which involves removing cycles with amplitudes smaller than a given threshold range from the actual data [14]. In present paper, the data is the observed load history measured at the hydraulic cylinder of a wheel loader as shown in Fig. 3(a). The observed load history contained 120 operating cycles with 9389 turning points (TPs). We select 0.5 amplitude range as a threshold range of the cycles. After rainflow data-reduction, the number of TPs was reduced obviously to 3300, as shown in Fig. 3(b). Because of relatively smooth movement in the full load transporting S2 and no load transporting S4, the amplitudes of most cycles are smaller than 0.5 amplitude range. As a result, there are 5068 TPs have been removed in this two sections that account for 83.2% of all the removed TPs.

As mentioned in Section 2, the overall measured load history is non-stationary and each operating section is stationary. For the non-stationary load history, as the statistics of load histories are not constant with respect to time, statistical methods relative to random loads like rainflow counting and extreme value extrapolation cannot be applied. However, each operating section is stationary with its own mean and variance [13, 15]. Therefore, each stationary operating section can be extracted from the load history after rainflow data-reduction and then statistical treatments for each operating section can be performed. As shown in Fig. 4, it can be clearly seen that each operating section (S1, S2, S3, S4) extracted from the load history after rainflow data-reduction is stationary.

3.2 Extreme loads extrapolation

Extreme loads occur rarely in engineering vehicles, they could not be obtained in a limit test. As is known, the extreme loads cause substantial damage of components and have a great effect on the final determination of fatigue damage. Therefore, the extreme loads should be taken into consideration in the simulation process. Generally, statistical approach is used to describe the occurrence probability of the extreme values of measured loads. To estimate the extreme values, the peak over threshold (POT) method is adopted in the present paper.

The schematic diagram of POT extrapolation is shown in Fig. 5. The black line is the observed signal and the blue line is the extrapolated extreme value. The horizontal dashed lines represent the defined threshold levels u. Then the TPs are extracted from the load history and those TPs above the high threshold level $u_{\max}$ (below the low threshold level $u_{\min}$) are taken as the extreme values to extrapolate the amplitudes randomly from a distributional model. A suitable approximate distributions for modeling the excesses $z_i = x_i - u \in \mathrm{Dis}(m)$, where $m = \frac{1}{n}\sum_{i=1}^{n} Z_i$ is the mean excesses over u, which is

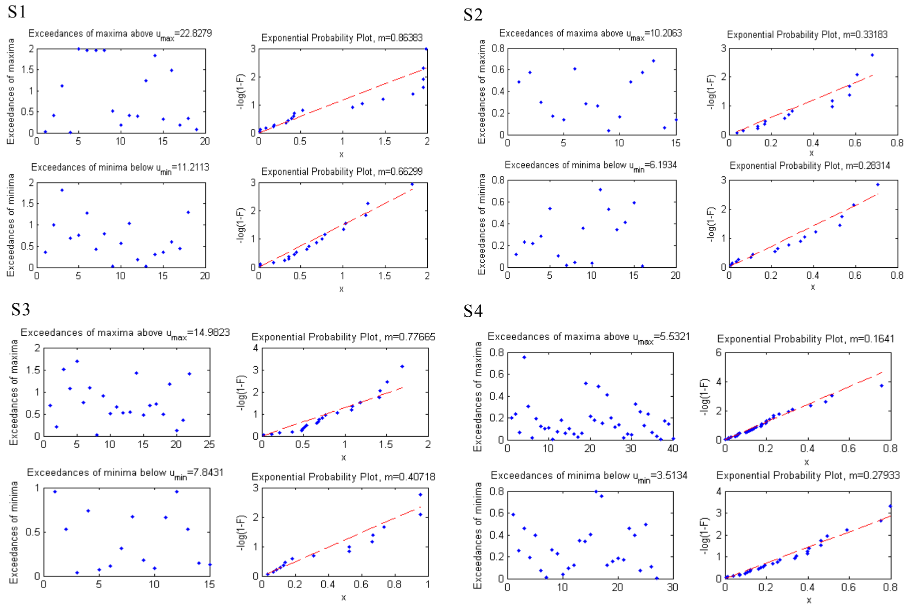


Fig. 6. Determination of the upper and lower limit threshold in each operating section.

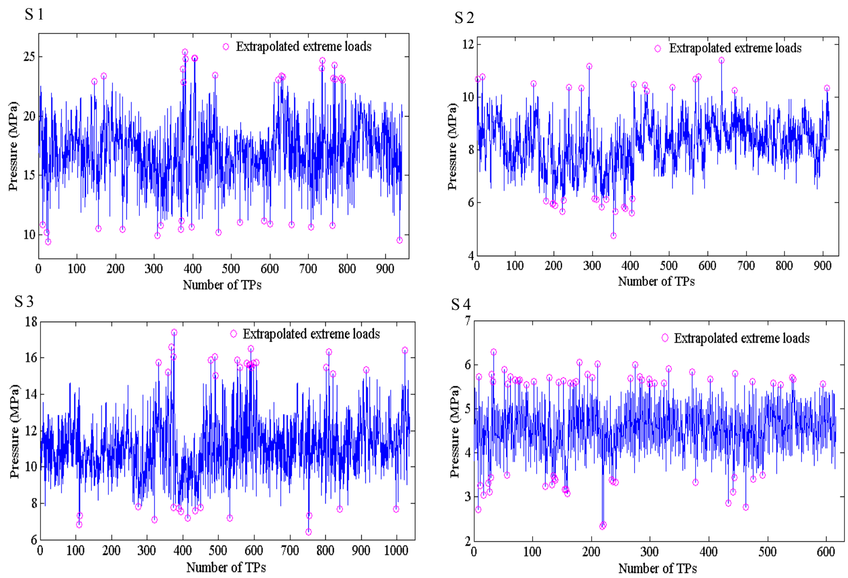


Fig. 7. Extrapolated load histories of each operating section.

the so-called threshold stable distributions of the Generalized Pareto Distribution (GPD) with cumulative distribution function $F(z)$ [11, 16].

$$F(z) = 1 - (1 + \frac{\gamma z}{\sigma})^{-\frac{1}{\gamma}} \tag{1}$$

where σ is the scale parameter, and γ is the shape parameter.

Mathematically, extreme value approximations are formulated as asymptotic results. In actual, the exponential distribution of excesses is equivalent to modeling the global maximum as a GPD, which works well in many applications [11].

$$F(z) = 1 - \exp\left(-\frac{z}{m}\right) \tag{2}$$

There is no standard choice of the threshold u, which should be selected based on engineering experience. At present, a default choice of exceedance number k that works well in many cases is $k = \sqrt{N_0}$, where N_0 is the number of cycles of the load history [11].

According to the above theory, the threshold u of each operating section is estimated as shown in Fig. 6, where the observations follow approximately the straight line so that the agreement is good. Further, as shown in Fig. 7, the load histories of each operating section above threshold $u_{\max}$ or below the threshold $u_{\min}$ are extrapolated to random values according to the estimated exponential distributions using the POT method.

3.3 MCMC simulation

MCMC simulation is a method that involves the use of random numbers to obtain data series with given probability distributions based on Markov chain. Therefore, at first, the Markov chain model of each operating section after extrapolation must be established.

In a realistic loading history, the load at a certain time instant is random, and the load or load range at a adjacent time instants may also be correlated; this can be modeled as a discrete time Markov chain $\{X_n\}$, where an ordered sequence of random loads observed at discrete time instants $\{t = t_1, t_2 \cdots t_n\}$ has a finite set of discrete levels $\{u = u_1, u_2 \cdots u_n\}$, called states. For a Markov chain $\{X_n\}$, the value $X_{k+1} = u_{k+1}$ at future time t_{k+1} depends only on the value $X_k = u_k$ at present time t_k, but is unrelated to the past values; that is,

$$P\left\{X_{k+1} = u_{k+1} \middle| X_1 = u_1, X_2 = u_2, \cdots, X_k = u_k\right\} \\ = P\left\{X_{k+1} = u_{k+1} \middle| X_k = u_k\right\}. \tag{3}$$

Note that the fatigue load history is a series of TPs, that is, formed by minimum-maximum-minimum… and so on. Therefore, the sequence of TPs is denoted by process $\{X_n^{TPs}\}$, that is,

$$\begin{cases} X_{2k} = m_k \\ X_{2k+1} = M_k \end{cases} \tag{4}$$

where X_{2k} is a minimum at time t_{2k} and X_{2k+1} is a maximum at time t_{2k+1} [17].

The evolution of the Markov chain is then described completely by its transition probabilities P_{ij}:

$$p_{ij} = P\{X_{2k+1} = u_j \middle| X_{2k} = u_i\}. \tag{5}$$

The set of its transition probabilities can be arranged into the following matrix:

$$P = (p_{ij})_{i,j=1}^n, \text{ with} \sum_{j=1}^n p_{ij} = 1. \tag{6}$$

The vector $\pi = (\pi_i)_{i=1}^n$ is called a stationary distribution of $\{X_n\}$, given by a unique solution to the equation system:

$$\begin{cases} \pi = \pi P \\ \sum_{i=1}^n \pi_i = 1. \end{cases} \tag{7}$$

The main steps of MCMC simulation can be summarized as follows:

First, the Markov chain model is established, and the transition probability matrix is calculated.

Second, the cumulative probability transition matrix P_{cum} is calculated from the following formula:

$$P_{cum,ij} = \sum_{l=1}^{j} p_{il} \tag{8}$$

where each row i of P_{cum} corresponds to the discrete cumulative distribution function for the next transition.

Third, given an initial state i simulated from stationary distribution π, to sample the next state, a random value between 0 and 1 is generated using a uniform random number generator. This random value is then compared with the elements of the *ith* row of the P_{cum} matrix. Assuming this number falls between elements $j-1$ and j, state j is chosen as the next state.

Fourth, the actual load inside state j can be obtained using the following relation:

$$X = X_{j-1} + r(X_j - X_{j-1}) \tag{9}$$

where X_j and X_{j-1} are the load boundaries of state j, and r is the uniform random number.

Given the observed load histories of each operating section shown on the left side of each picture in Fig. 8, the corre-

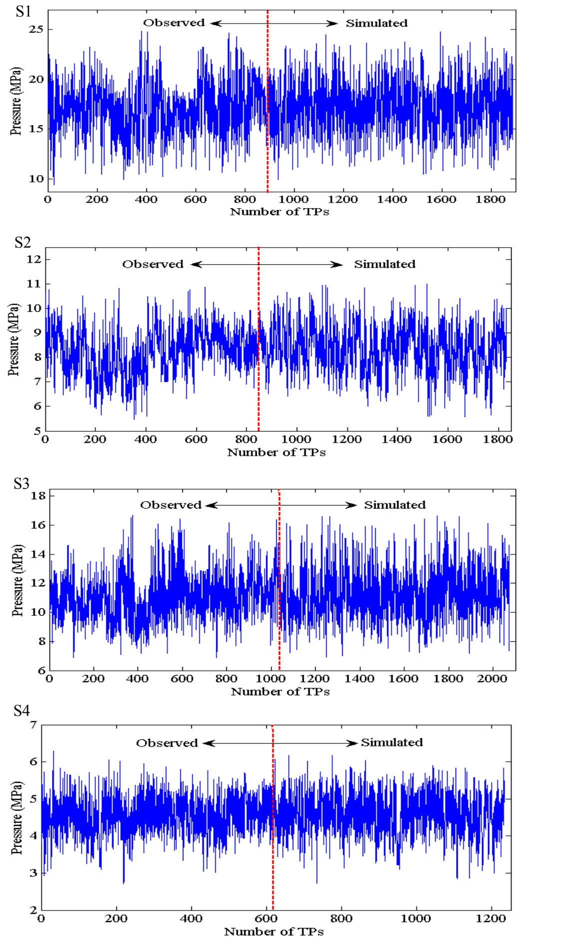


Fig. 8. Simulated load histories of each operating section compared with the observed load histories.

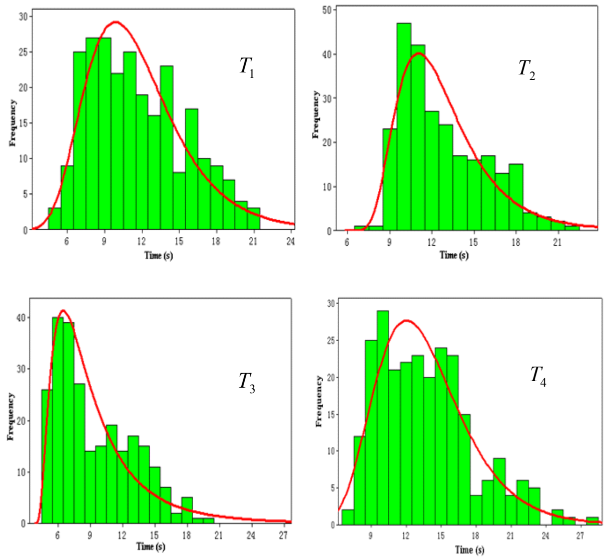


Fig. 9. PDF of the time variable *T* of each operating section.

sponding simulated load histories are shown on right side of Fig. 8. One can see that good agreement is obtained by MCMC simulation method.

In the following cyclic simulation process, we will take 50-fold extrapolated load histories of each operating section as the input data of simulation. In this way, the information of the extrapolated load history can be presented sufficiently.

3.4 Probability density functions (PDF) of the time variable T of each operating section

For the sake of cyclic simulation of the overall non-stationary load history, the simulation length T of each operating section must be investigated. It should be mentioned that the simulation length T is a variable that distributes in a certain range. In this section, the PDF of each time variable (namely T_1, T_2, T_3, and T_4) is obtained using statistical methods. The basic steps are as follows:

(1) Extract the time data of each operating section from observed non-stationary load history.

(2) Obtain the histogram of each time variable from the time data.

(3) Obtain the PDF by means of histogram fitting.

Fig. 9 depicts the PDFs of T_1, T_2, T_3, T_4 belonging to each operating section as well as the corresponding histograms. They all follow logarithmic normal distributions, the estimated parameters are shown in Table 1.

3.5 Cyclic simulation of the overall load history

With the simulated load histories of each operating section and the PDFs of time variable T, the overall load history can be generated by a cyclic simulation method. That is, the sequence of simulation is in accordance with S1-S2-S3-S4-S1-S2-S3-S4-…, and loops in turn. The simulation length T of each operating section can be generated stochastically by Monte Carlo method. For didactic reasons, the directed graph of cyclic simulation is shown in Fig. 10.

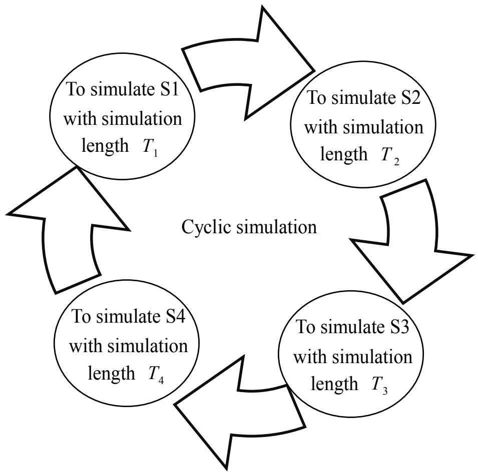
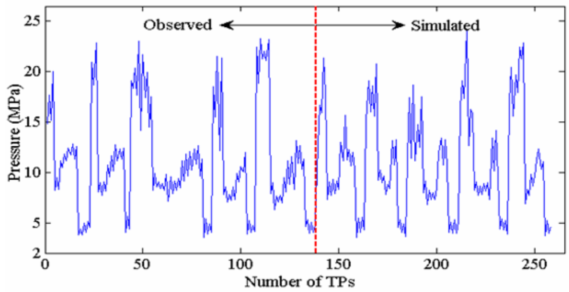
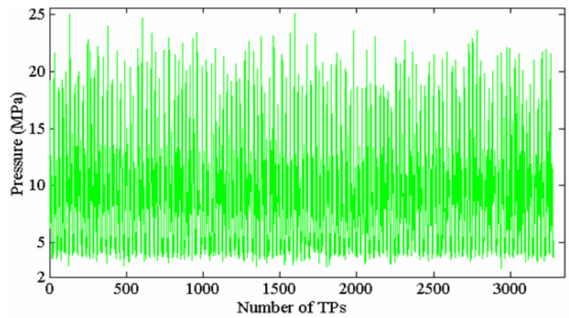


Fig. 10. Directed graph of cyclic simulation.



(a)



(b)

Fig. 11. Simulated results: (a) observed load history with 5 operating cycles and the corresponding simulated load history; (b) simulated load history with 120 operating cycles.

Monte Carlo is a kind of numerical simulation which requires some specified probability distribution for uncertain variables before simulation. The PDFs of the time variable T of each operating section regarded as input quantities are given in Section 3.4. Therefore, the time series of each operating section can be produced by the Monte Carlo method.

In Fig. 11, the simulated load histories with 5 operating cy-

Table 1. Statistical characteristics of the observed and simulated load histories.

Data	Cycles	Max (MPa)	Min (MPa)	Mean (MPa)	S.D.	RMS (MPa)
Observed	1650	24.8139	2.8750	10.8107	4.8037	11.8296
Simulated	1641	25.1279	2.7446	10.5477	5.0187	10.5214

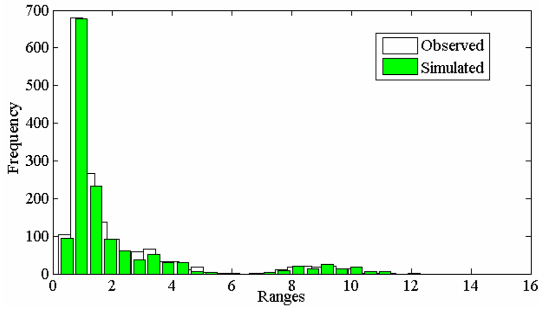


Fig. 12. Histograms of amplitudes from the rainflow matrixes of the observed and simulated load histories.

cles and 120 operating cycles are given. From Fig. 11(a), it can be seen that the cyclic characteristic can be reconstructed well. It can be seen in Fig. 12 that the histogram of amplitudes from a rainflow matrix of the simulated load history (see Fig. 11(b)) fits that of the observed load history (see Fig. 3(b)) very well.

The statistical characteristics of observed and simulated load histories are listed in Table 2. The statistical characteristics of simulations adequately match that of the observed load history. As is shown, due to the simulation after extrapolating extreme loads of each operating section, the max of the simulated load history is larger than that of the observed, and the min of the simulated load history is smaller than that of the observed. Besides, as shown in Fig. 13, by comparing the mean, standard deviation (S.D.) and root mean square (RMS) of each 10 operating cycles between the observed and simulated load histories, we find that the statistical characteristics of simulations match that of the observed load history in dynamic process as well.

4. Conclusions

In the current paper, non-stationary load histories of engineering vehicles are generated by a newly proposed cyclic simulation approach. Additionally, the extrapolation of extreme values is added into the simulation process, taking into consideration the extreme loads which could not be obtained in a limit test. The applicability of the newly approach is assessed on the observed load history measured at the hydraulic cylinder of a wheel loader, which is a typical example of engineering vehicles. Good agreement between the observed and simulated load histories is achieved, and the cyclic characteristic is reconstructed well (see Fig. 11(a)). From comparative analysis of the observed and simulated load histories (see Ta-

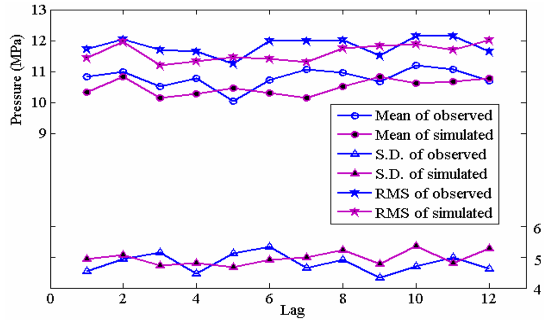


Fig. 13. Statistical characteristics of observed and simulated load histories in dynamic process.

ble 2, Fig. 12 and Fig. 13), we can draw the conclusion that they have near-identical statistical characteristics, which can in turn indicate that the proposed method can serve as a tool to generate analogous non-stationary load histories in engineering vehicles. Due to adding the extrapolation of extreme values into the simulation process, the extreme loads can be simulated approximately, which make the simulation results closer to the real condition.

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