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Load Description and Damage Evaluation using Vehicle Independent Driving Events

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Abstract

We consider the loads that are related to steering events, and focus on the events that cause high forces on steering components. The load is simplified by keeping the extreme force value for each driving event. We define a simplified stochastic model for the load by modeling the extreme value for each driving event by a random variable. We give formulas to compute the theoretical load spectrum and the expected fatigue damage caused by the driving events. Further, in a sensitivity study we investigate how much the expected damage depends on the variability of parameters of the proposed model.

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1. Introduction

In vehicle engineering, durability is an important aspect of designing a vehicle with high quality in its components. Therefore, considering the service loading conditions is necessary. In addition, in fatigue design the loads need to be assessed. By describing the load environment, the customer usage and the vehicle dynamics one can define the load conditions [1].

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Nomenclature

λ	hidden Markov model parameters	d_β	damage intensity
$D_\beta(x)$	damage index	$E[D_\beta(X)]$	expected damage index
α, β	material constants for Palmgren–Miner’s rule	$N^{rc}_\beta(u, v)$	rainflow counting distribution
u, v	lower and upper ranges for cycle range	$\mu^{osc}(u, v)$	intensity of interval crossings

For vehicle companies, it is important to characterize the way that the trucks have been used. They want to describe the usage of the trucks in a way that it is independent of the vehicle. The loads will be different for different usage of trucks and for different driver’s behavior. A driver can affect the load by changing the speed, braking or adapting to the curves. These behaviors can be characterized as driving events and can be assessed using measurements obtained from specially equipped vehicles on a test track. Measuring the load on each truck is expensive. However, they want to measure and identify activities of the driver and specify the relevant events occurring on the road. To identify the events we need to use the information available for all vehicles by means of CAN (Controller Area Network) bus data. If we define the events such as static steering by using the information from CAN data, we can detect the amount of events that are occurring in customer vehicles. Then, it is possible to calculate the forces generated from the same kind of events by repeating the loads under well-defined conditions on a proving ground. By using the force signal we can clarify which occasions will generate high forces.

We have proposed a stochastic model of loads related to the steering events such as curves and maneuvers, which cause large forces acting on steering components. An explicit formula for calculating the expected fatigue damage based on identified driving events is given, see also Maghsood and Rychlik [2]. The expected damage depends on the frequencies of driving events and the expected value of the extreme force during an event. The model consists of two parts; description of the sequence of steering events and the model for the extreme loads occurring during the events. The sequence of steering events is modeled by means of a Markov chain. This is a vehicle independent part of the load. For simplicity, the extreme forces during the events are assumed to be statistically independent. Their distributions may depend on the type of steering event, e.g. (left, right) cornering, slow maneuver to the right or to the left etc. The parameters of the distributions are vehicle dependent and need to be estimated using dedicated measurement campaigns or test track measurements. In the examples in Sections 5 and 6, the Rayleigh distribution will be used to describe the variability of extreme forces. Further, the uncertainty in fatigue damage due to model parameters will be discussed.

The paper is organized as follows. In Section 2 hidden Markov models (HMMs) based algorithm to detect the steering events is reviewed. The proposed model for loads and means to calculate the expected damage are described in Sections 3 and 4. Examples and their results for measured data are shown in Section 5. In Section 6 the sensitivity analyses are investigated. Conclusions are presented in Section 7.

2. Detection of the steering events

Hidden Markov models (HMMs) have been proposed for detection of steering events such as curves and maneuvering using on-board logging signals available on trucks, such as lateral acceleration, vehicle speed and steering wheel angle. The idea is to consider the current driving event as the hidden state and set up the model based on them, see Maghsood and Johannesson [3, 4].

We have used a discrete HMM, $\lambda = (A, B, \pi)$ where λ represents model parameters which contain the transition matrix, the emission matrix and the initial state distribution. The parameters must be estimated to characterize the model, see Rabiner [5] for more details.

In an HMM, a training set is used to estimate the parameters of the model, while a test set is used to validate the model. A training set consists of all necessary information for estimating the model parameters. In the examples, the training set contains all history about the curves such as the start and stop points of them. Fig. 1 shows a lateral acceleration signal and the corresponding identified hidden states process.

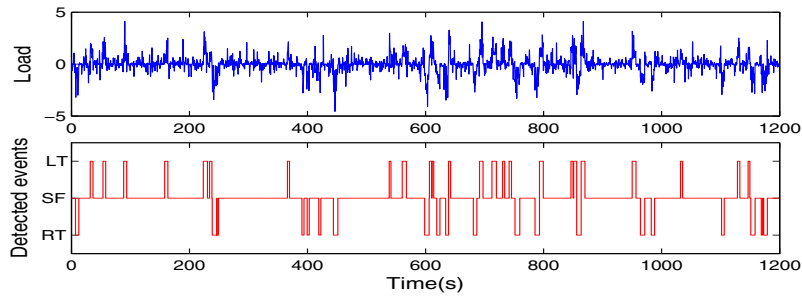


Fig. 1. Lateral acceleration signal and the corresponding detected events.

3. Random model of lateral loads based on steering events

Modeling of the external loads is an important aspect in durability studies of vehicle components. The approach taken here is to approximate the load by a vehicle independent sequence of steering events, here representing Left and Right steering (SL, SR) or Left and Right turns (LT, RT). In both cases the two events are separated by a section when wheels have approximately zero turning angle, which is called Straight forward (SF). Thus, a reduced load can be defined by keeping the extreme value for each left and right event and set zero for each straight forward event. The most extreme value of the load will be modeled by a random variable Y_i . First the variability of the sequence of steering events is modeled by a Markov chain Z_i having two states "1" and "2", then the values of extreme forces during events will be modeled. The Markov chain is defined by a transition matrix $P = (p_{ij})$, $i, j = 1, 2$, where p_{ij} denotes the transition probabilities between the states.

Let $M_i, i = 0, 1, 2, \dots$ be a sequence of independent and identically distributed (iid) positive random variables while $m_i, i = 0, 1, 2, \dots$ denotes the negative random variables. Assume that the three sequences $\{Z_i\}_{i=0}^{\infty}$, $\{M_i\}_{i=0}^{\infty}$ and $\{m_i\}_{i=0}^{\infty}$ are independent. The process Z_i is vehicle independent while M_i and m_i depend on the vehicle, driver etc. The sequence of extreme loads $Y_i, i = 0, 1, 2, \dots$, is defined by:

$$Y_i = \begin{cases} M_i, & \text{if } Z_i = 1, \\ m_i, & \text{if } Z_i = 2. \end{cases} \quad (1)$$

Finally, we can define the random load $X_i, i = 0, 1, 2, \dots$ by adding zeros between Y_i and Y_{i+1} for each straight forward event:

$$X_i = \begin{cases} 0, & \text{if } i \text{ is odd,} \\ Y_{i/2}, & \text{otherwise} \end{cases} \quad (2)$$

4. Fatigue damage index

The aim is to compute the expected damage based on the detected driving events. To evaluate the model, we will compare the estimated damage index from the measured forces using rainflow method with the expected damage from the proposed load model. To calculate the damage, we have used forces which are measured from specially equipped vehicles on a test track. First we will review some models and methods on fatigue damage.

Assume that the measured load X is given in form of time series $x_i, i = 0, 1, 2, \dots, n$. The risk for fatigue failure in the material is often measured by means of a damage index which can be computed by Palmgren-Miner rule [6, 7], viz.

$$D_{\beta}(x) = \sum_{i=1}^N \frac{1}{N_i} = \alpha \sum_{i=1}^N h_i^{\beta} \tag{3}$$

where N_i is the number of cycles having ranges h_i to failure estimated in constant amplitude tests and presented in form of S-N curve.. The parameter α is the fatigue strength of the material and β is the damage exponent.

The variability of the load is modelled by means of random processes. Therefore, the measured load x is one of many possible realizations of the process. For the random loads, the rainflow ranges become random variables and the damage index is a random quantity too. The variability of the rainflow cycles can be described using a cumulative histogram $N^{rfc}(u, v)$ which is called the rainflow counting distribution. The rainflow counting distribution $N^{rfc}(u, v)$ is equal to the number of times that the load $x_i, i = 0, 1, 2, \dots, n$, crosses an interval $[u, v]$ in upward direction, denoted by $N_n^{osc}(u, v)$. The equality between the rainflow counting distribution and the interval crossing was shown independently in [8] and [9].

The damage intensity can be used to measure the severity of the random load and it can be computed using the intensity of interval crossings:

$$\mu^{osc}(u, v) = \lim_{n \rightarrow \infty} \frac{E[N_n^{osc}(u, v)]}{n}, \tag{4}$$

then the damage intensity is

$$d_{\beta} = \beta(\beta - 1) \int_{-\infty}^{\infty} \int_{-\infty}^v (v - u)^{\beta - 2} \mu^{osc}(u, v) du dv. \tag{5}$$

The main result is an explicit formula for $\mu^{osc}(u, v)$ based on the random load X_i :

$$\mu^{osc}(u, v) = \frac{1}{2} \begin{cases} \pi_2 P(m_1 < u), & u < v < 0 \\ \pi_2 P(m_1 < u) p_2(u, v), & u \leq 0 \leq v \\ \pi_1 P(M_1 > v), & 0 < u < v \end{cases} \tag{6}$$

where $p_2(u, v)$ is the solution to the equation system

$$\begin{aligned} p_1(u, v) &= p_{11} P(M_1 > v) + P(M_1 \leq v) p_{11} p_1(u, v) + P(m_1 \geq u) p_{12} p_2(u, v), \\ p_2(u, v) &= p_{21} P(M_1 > v) + P(M_1 \leq v) p_{21} p_1(u, v) + P(m_1 \geq u) p_{22} p_2(u, v). \end{aligned} \tag{7}$$

see [6] for more details and prof of formula (6).

5. Example

The results are presented for maneuvering events. The curves were also studied in [2] but the results will not be presented here. The maneuvering events, i.e. driving in or out of a parking lot, standing still but turning steering wheel,

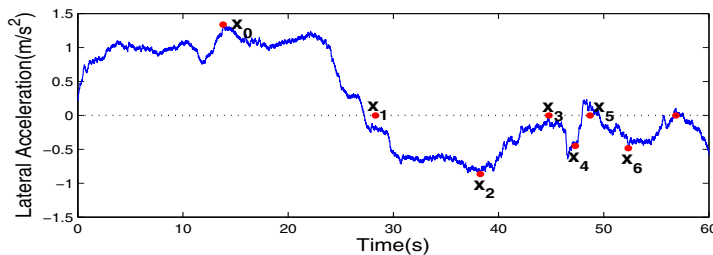


Fig. 2. Reduced load represented by dots compared with observed load, lateral acceleration, represented by the irregular solid line.

are considered as the events which will happen in speed less than about 10 km/h. Here, three maneuvering events are considered; Steering Left (SL), Steering Right (SR) and Straight Forward (SF). The measured loads are denoted by x^{obs} . First, the steering events were detected using HMM algorithm, then the extreme loads during events were found. We assume that each event follows by a driving straight section. The signal consisting of the extreme loads during steering events and zeros for section when vehicle is driving straight will be denoted by $x = (x_0, x_1, \dots, x_n)$ and called the *reduced load*. In Fig. 2 part of measured load x^{obs} (lateral acceleration) is shown as the solid line while the reduced load x by dots.

The link rod force is used as the load and it is shown in the top plots of Fig. 3a. The extreme forces are negative, positive and zero in the three states SR, SL and SF, respectively. In the figure stars are the extreme rod forces, occurring during maneuvers, constituting the reduced load. In the lower plot of Fig. 3a, the detected time periods with 21 detected maneuvering events are shown.

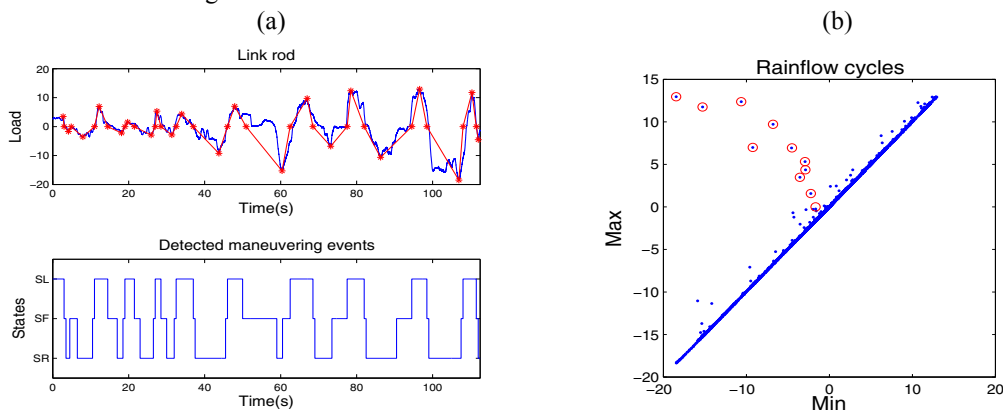


Fig. 3. (a) Top: solid irregular line is the measured link rod force while stars represent the reduced load. Bottom: Detected maneuvers. (b) Dots - the rainflow cycles found in the measured link rod force. Circles - the rainflow cycles counted in the reduced load.

The rainflow cycles have been found both in the load and in the reduced load and compared in Fig. 3b. The rainflow cycles found in the measured link rod force are marked as dots. One can see that there are few large cycles and many very small ones. The rainflow cycles found in the reduced load are presented as circles. As can be seen in Fig. 3b, all large cycles found in the link rod force are also found in the reduced load and hence one can expect that the damage index computed for the measured load and the reduced load should be very close.

The estimated transition matrix according to the detected maneuvers is

$$P = \begin{pmatrix} 0 & 1 \\ 0.9 & 0.1 \end{pmatrix}$$

The Rayleigh distributions have been fitted to positive and negative values, respectively. The estimates of the parameters of Rayleigh distributions were very close. The difference between the parameter values were not significant hence the average value (6.1) of the parameters have been used.

Table 1 shows a comparison of the damage indexes $D_\beta(x^{obs})$ computed for measured load, $D_\beta(x)$ for the reduced load and the expected damage index $E[D_\beta(X)]$ for the random model of the reduced load. Damage indices $D_\beta(x^{obs})$ and $D_\beta(x)$ are given in columns 2 and 3. As expected these are almost identical. We conclude that the reduced load models well the variability of the measured load. Further, the expected damage of the model is quite close to the measured one.

Table 1. Comparison of damage indices $D_\beta(x^{obs})$ computed for the measured load, $D_\beta(x)$ for the reduced load and the expected damage index $E[D_\beta(X)]$.

Damage	$D_\beta(x^{obs})$	$D_\beta(x)$	$E[D_\beta(X)]$
$\beta = 3$	9.39×10^3	9.34×10^3	8.35×10^3
$\beta = 5$	1.70×10^6	1.70×10^6	1.47×10^6

In Fig. 4a, the load spectra estimated from the measured link rod force and the reduced load are compared with the theoretical load spectrum. As can be seen in Fig. 4b, where the load spectra for 10 simulated loads are compared with the theoretical load spectrum and the load spectrum of the reduced load, the differences between the measured spectrum and the expected one does not seem to be significant.

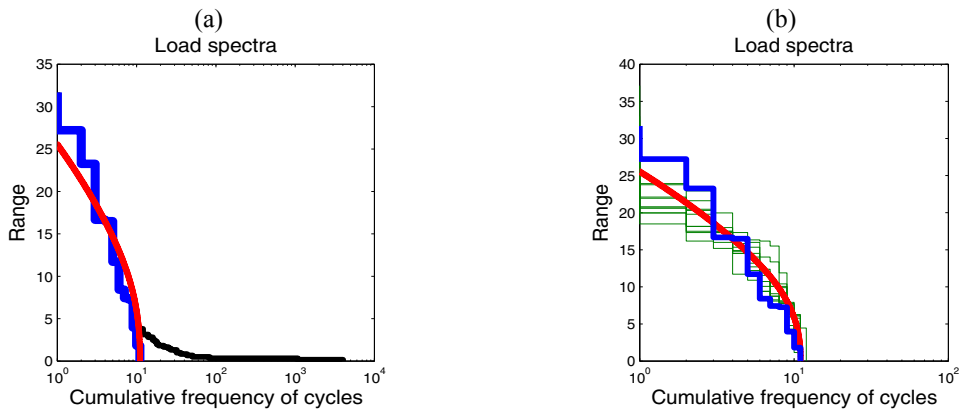


Fig. 4. (a) The regular solid line is the theoretical load spectrum. The stairs like functions are the load spectra found in measured link rod force and the reduced load. (b) Load spectra for 10 simulated loads compared with the theoretical load spectrum and the load spectrum of the reduced load (the thick stairs like line).

6. Sensitivity analysis of the damage index

As it was mentioned before, the sequence of steering events is modeled by a Markov chain with transition matrix P . This sequence is a vehicle independent part of the load. The extreme forces during the events are assumed to be statistically independent, but their distributions depend on the type of steering event. The parameters of the distributions are vehicle dependent and need to be estimated using dedicated measurement campaigns or test track measurements. In the examples, Rayleigh distributions have been fitted to positive and negative values. Now suppose that both distributions have the same parameter σ , viz.

$$P(M_1 > v) = e^{-\frac{1}{2}(\frac{v}{\sigma})^2}, v \geq 0 \quad P(m_1 < u) = e^{-\frac{1}{2}(\frac{u}{\sigma})^2}, u \leq 0 \tag{8}$$

then the load can be written as a scaled standard load, $X = \sigma \hat{X}$, where \hat{X} is a reduced load with standard Rayleigh random variables, $P(R > r) = e^{-r^2/2}$. Therefore, the oscillation intensity can be written as a scaled one, namely

$$\mu^{osc}(u, v) = \hat{\mu}^{osc}\left(\frac{u}{\sigma}, \frac{v}{\sigma}\right). \tag{9}$$

Further, the damage index can be calculated as $d_\beta = \sigma^\beta \cdot \hat{d}_\beta$, where \hat{d}_β is the expected damage computed by the standard Rayleigh distribution. This means that the expected damage index is a factor of the parameter σ to the power β .

Here, we will consider two types of uncertainties. The variability of the load environment will manifest in the transition matrix P and the vehicle dependent variability in the parameter σ of the Rayleigh distribution. In the following subsections we will study how much the expected damage will vary because of variability of matrix P and parameter σ . We will also investigate the statistical uncertainty of the estimation of σ . In fatigue reliability evaluation using the load-strength concept often the log-normal distribution is used, see [1, Chapter 7]. Therefore, the uncertainty in damage will be measured in terms of the standard deviation of the logarithmic damage, which corresponds to the relative uncertainty in damage (or fatigue life).

6.1. Variability of the transition matrix P

To examine how much the expected damage will depend on the transition matrix P , three different Markov chains have been used to model the sequence of driving events.

- First, assume that we always go from left to left. This would be the case with the smallest possible damage, since all minima are equal to zero. The expected damage is $E[D] = nE[R^\beta]$, where n denotes the number of turns and R represents the standard Rayleigh random variable for the maximum force.
- Second, consider that the events change each time. In this case, $p_{12} = p_{21} = 1$, and we will get the maximum damage for this type of Markov chain. The oscillation intensity $\mu^{osc}(u, v)$ given in Eq. (6) can be simplified to

$$\mu^{osc}(u, v) = \frac{1}{4} \begin{cases} P(m_1 < u), & u < v < 0 \\ \frac{P(M_1 > v)P(m_1 < u)}{1 - P(M_1 \leq v)P(m_1 \geq u)}, & u \leq 0 \leq v \\ P(M_1 > v), & 0 < u < v \end{cases} \tag{10}$$

- Finally, assume that left and right turns occur independently of the past with probabilities $p_{ij} = 0.5$, and Eq. (6) simplifies to (see also [10])

$$\mu^{osc}(u, v) = \frac{1}{4} \begin{cases} P(m_1 < u), & u < v < 0 \\ \frac{P(M_1 > v)P(m_1 < u)}{P(M_1 > v) + P(m_1 < u)}, & u \leq 0 \leq v \\ P(M_1 > v), & 0 < u < v \end{cases} \tag{11}$$

The expected damage values for the three different cases have been summarized in Table 2. Here, we have considered standard Rayleigh distributions for negative and positive values and the number of events is $n = 100$.

Table 2. Expected damage calculated from the three different Markov chains.

Damage	Minimum	Independent	Maximum
$\beta = 3$	0.05×10^3	0.14×10^3	0.17×10^3
$\beta = 5$	0.06×10^3	0.72×10^3	0.80×10^3

The two extreme cases will be used to calculate the uncertainty in damage by assuming a uniform distribution between the minimum and maximum values, viz. for $\beta = 3$

$$\tau_P = \frac{\ln d_{max} - \ln d_{min}}{\sqrt{12}} = \frac{\ln 0.17 - \ln 0.05}{\sqrt{12}} = 0.35 \tag{12}$$

which can be interpreted as corresponding to 35% relative uncertainty in damage, as the natural logarithm is used.

6.2. Statistical uncertainty of parameter σ

Suppose that we estimate the parameter σ based on n observations, then we may ask how much the estimation uncertainty of parameter σ impacts the damage. The estimate of parameter σ for a Rayleigh distribution is $\hat{\sigma} = \sqrt{2/\pi} \bar{X}$ and its distribution is approximately normal $N(\sigma, \frac{4-\pi}{n\pi} \sigma^2)$. Thus, the uncertainty in damage can be approximated using Gauss' approximation formula, viz.

$$\tau_{\sigma, stat} = \text{Var}[\ln \hat{\sigma}^\beta] = \beta \cdot \text{Var}[\ln \hat{\sigma}] \approx \beta \cdot \sqrt{\frac{4-\pi}{n\pi}} = 0.29. \quad (13)$$

with an example for a short signal with $n = 30$ maneuvering events and $\beta = 3$, corresponding to a typical length of the measurements.

6.3. Variability of parameter σ

For different measurements of maneuvering events, we have found different estimates of parameter σ , say $\sigma_1, \sigma_2, \dots, \sigma_l$ for l different measurements. The uncertainty in damage due to the variability in the estimated σ is computed as the sample standard deviation, viz.

$$\tau_\sigma = \text{std}(\ln \sigma^\beta) = \beta \cdot \text{std}(\ln \sigma) = 3 \cdot 0.18 = 0.56 \quad (14)$$

for an example with $\beta = 3$ and estimated σ -values 6.15, 6.05, 9.40, 8.96, 7.76, 6.37, 6.72. However, the uncertainty τ_σ includes both the variability and the statistical uncertainty of σ . Thus, the pure variability can be estimated as

$$\tau_{\sigma, var} = \sqrt{\tau_\sigma^2 - \tau_{\sigma, stat}^2} = 0.46.$$

7. Conclusion

A reduced load, i.e. a sequence of the most extreme forces during steering events, was introduced. A random load modeling the variability of the reduced load was proposed. The sequence of steering events, which is vehicle independent information, was modeled using a two states Markov chain. The extreme forces occurring during the steering events were modeled by means of independent Rayleigh distributed variables. For the model, an explicit formula for the expected fatigue damage was presented. The proposed random model depends only on four parameters which could be used to classify and compare the severity of driving environments.

The results were validated using measured data. The slow speed maneuvering events were detected. All large rainflow cycles found in measured load were also counted in the reduced load. Hence the reduced load can be used to predict fatigue damage of steering components. The observed load spectrum did not significantly differ from load spectra found in the simulated loads. We conclude that the proposed random load accurately describe the variability of the rainflow ranges for the considered measured loads.

A sensitivity study was conducted to see how much the expected damage depends on the parameters of the proposed model.

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