Vibration-Based Symptoms in Condition Monitoring of a Light Rail Vehicle Suspension

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ABSTRACT

The aim of the presented work was to determine the suitable vibration-based symptoms for the identification of a light rail vehicle suspension technical state, as well as the development of appropriate methodology to use the information contained therein. In the numerical phase, low-frequency mathematical models of typical light rail vehicles were used. After validating main model characteristics, many simulations were made, to find suitable measures for each suspension defect, modeled as the deviation of stiffness and damping parameters from nominal values. During the experimental phase, a prototype of the monitoring system was installed on the vehicle in normal operation, with suspension elements having different parameters. The analysis of the obtained results led to the development of the appropriate methodology and suitable vibration-based symptoms for light rail vehicle suspension monitoring.

INTRODUCTION

Light rail systems have now their great return in many European cities – carrying an increasing number of people every year. In order to make a public transport competitive, it's very important to increase safety and ride comfort for passengers. Meanwhile the lack of officially accepted measures is one of the most significant obstacles to a successful implementation of a condition monitoring systems for light rail vehicles. Suitable symptoms are very important for the monitoring performance, including the sensitivity with respect to monitoring parameters, robustness to the environmental changes and reliability over the expected useful life.

To the most complicated problems of monitoring, belong those connected to the on-line monitoring of vehicle suspension, including problems of fault detection and identifications. Those problems were considered by many authors, e.g. [1÷5] and typical presented procedures of monitoring suspension defects are connected with the transmittance analysis of measurements made for every suspension element. Most publications on this topic are related to heavy rail vehicles and are not necessarily well

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suited for tramway systems. Also existing procedures and standards, concerning ride comfort and stability of classic rail vehicles, cannot be applied to tramways.

Responding to these needs, a technical state monitoring system of light rail vehicle and track is now being developed within a framework of a research project MONIT, as a complex solution for monitoring the technical condition of the vehicle. The system is based on a dispersed network of sensors installed on the vehicle, along with the data acquisition unit and a data server with the application of analysis and management of diagnostic data. The condition monitoring is based mainly on the acceleration signal analysis and all events are evaluated qualitatively.

MONITORING CONCEPT

General concept of the assumed diagnosis of a light rail vehicle condition is based on comparing the acceleration signal measured during the ride over the identical track section (e.g. crossings) or track sections having equivalent irregularities. It is possible, due to the fact that tramway lines are relatively short and there always exist some track sections causing transient responses of a tramway as a mechanical system. This transient phenomena analysis will allow to inspect the LRV mechanical state.

The general task of statistical treatment of simulation and experimental results was to investigate the possibility of inconsistency of two recorded signals. The first one was a pattern signal represented by the vehicle model with nominal values of selected parameters and the second one a model with faults (e.g. in the suspension). In our studies the following statistical measures were used: RMS, average, square, peak, peak-to-peak amplitude, shape coefficient, peak coefficient, impulse coefficient, clearance coefficient, standard deviation, kurtosis and interquartile range. Signal inconsistency was assumed as the relative value described by formula:

$$(1- D_F / D_N)*100\% \tag{1}$$

where D_F is statistical measure of vehicle with fault and DN is statistical measure of vehicle with nominal parameters.

NUMERICAL INVESTIGATION

During simulations phase, low-frequency mathematical models of different vehicles were used, with the vibration range up to 30 Hz approximately, slightly different from typical rail vehicles models. It is due to important difference in light rail vehicles construction compared to classic rail vehicles. Numerical simulations were performed for different light rail vehicles types with selected suspension faults scenarios, under different ride parameters, such as vehicle speed, load, track type etc.

For each of tens simulation cases, selected measures were calculated from the acceleration signal of each 36 numerical sensors located in different locations on a tested vehicle. A sample 3D graph is presented in Fig. 1, representing relative values of selected vibration-based measures for the secondary damper fault simulation. The vehicle speed in this case was about 18 km/h.

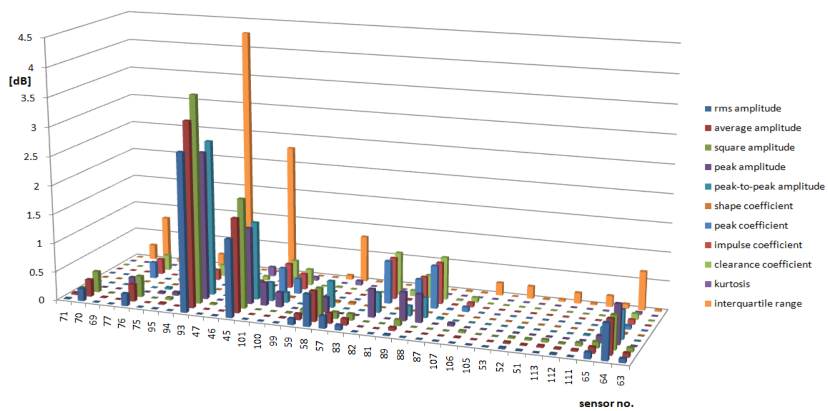

Figure 1. Selected measures relative values due to secondary damper fault.

Analyzing the graph above (and others graphs obtained for each suspension fault during the simulation phase) we can clearly assume, that for a given sensor location (in this case sensor no. 93 and 45, which are sensors located in the middle and on the right side of a bogie frame), some measures are more suitable than others for the condition monitoring of a light rail vehicle suspension (in this case RMS, average and square amplitude, as well as the shape coefficient). A similar graph, but for the simulation of fault in primary suspension, is presented in Fig. 2.

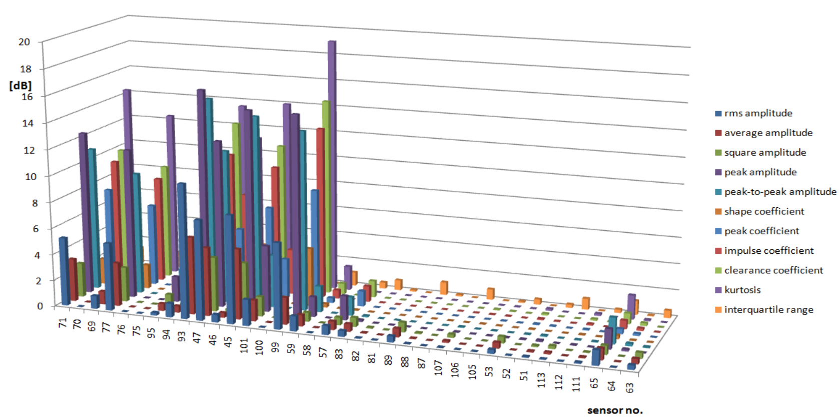

Figure 2. Selected measures relative values due to primary spring fault.

In this case, the best location for monitoring sensors is on the axlebox (sensors no. 69, 71 and 77) and/or on the bogie frame of the given bogie (sensors no. 45, 46, 47), while the best vibration-based measures are RMS and peak-to-peak amplitude.

EXPERIMENTAL PHASE – PRELIMINARY RESULTS

Preliminary data analysis

Selected data derived from three different days of tram operation and contained the information about the instantaneous speed of the vehicle and the values of eleven vibration-based measures from the acceleration signal in the Y and Z direction.

We can observe a very strong dependence of selected measures on the instantaneous tramway speed (Fig. 3). This relationship may mask the impact of technical state change on the measured symptoms.

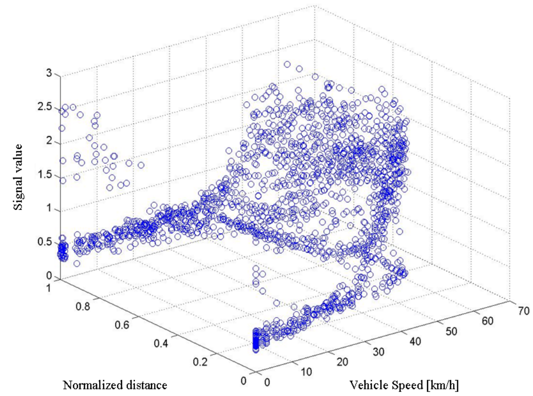

Figure 3. RMS values of vibration signal in the Z direction with regard to speed and the normalized distance from the initial position of the vehicle.

Unfortunately this particularly strong speed dependence concerns mainly the most useful diagnostic measures (e.g., RMS, square or mean amplitude). It relates less e.g. the shape or clearance coefficients, which, however, usually has less use in detecting changes in the technical state of the vehicle (Fig. 4a and 4b). Hence, the basic problem is to eliminate the impact of speed on the obtained vibration-based measures.

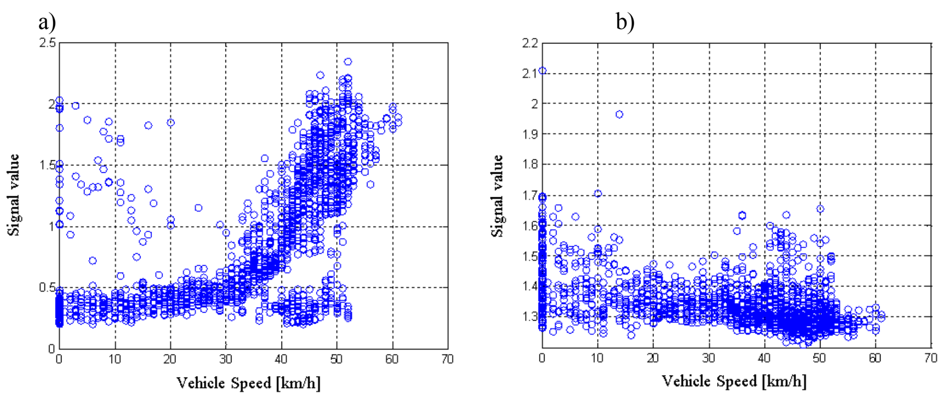

Figure 4. The mean value (a), and the shape coefficient (b) in a function of speed.

Improvement of the data quality

Since the analysis of available data shows that the position and the vehicle speed have the strongest effect on the selected measures, we applied some procedures for data selection in order to eliminate data from outside of a specified range. This will emerge measures of the best quality (in this case with the lowest variability). An important improvement in data quality can be achieved using a simultaneous selection due to the location of the vehicle and its speed. Rejection of the 25% of the initial and final track section and the reduction of data to the speed range 10 ÷ 40 km/h can be achieved acceptable results for more than the original number of symptoms (Fig. 5).

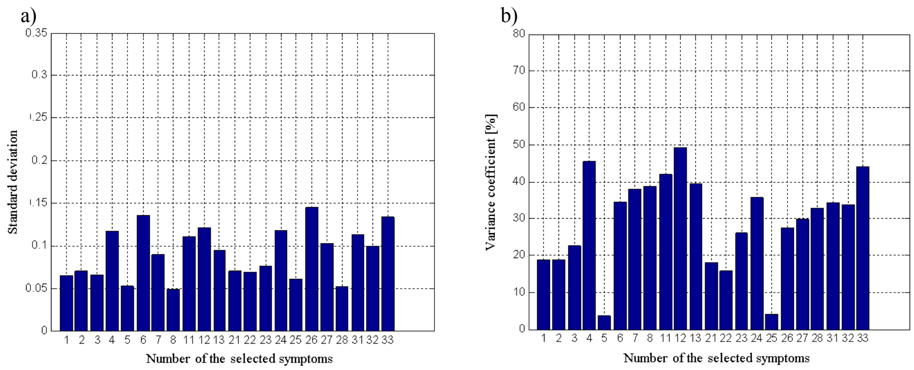

Figure 5. Standard deviation (a) and variation coefficient (b) of the selected measures - results obtained after the simultaneous selection of data due to the range of speed and the middle track section.

We can observe, that the simplest method of data selection can afford to improve their quality (standard deviation for preliminary data is shown in Fig. 8). To apply it in practice it is necessary to take the decision on the track section that will be considered as a reference one for the suspension monitoring. On this section, the vehicle should move with a uniform speed without acceleration. Furthermore, an appropriate range of vehicle speed for data selection should be include in the methodology.

Another possibility to improve results quality is to use PCA analysis to create a linear combination of the selected symptoms. PCA (Principal Components Analysis) is used in data mining for lossy compression of information. PCA used as a transformation of the original data varies a large amount of input data into a set of statistically independent components, with respect to their importance. After the transformation, the new space of observation preserves only the most important information, with the possibility to control the level of loss of information.

Typically, using PCA analysis we make a selection of the first U-eigenvalues and eigenvectors associated with them, replacing the original observation matrix with a matrix of smaller size. For this purpose, we use different assessment of the acceptable loss of information such as numerical threshold based on the expression:

$$\frac{\lambda_1 + \lambda_2 + \ldots + \lambda_U}{\sum_{i=1}^{P} \lambda_i} \tag{2}$$

where: λ_i is the i-th eigenvalue, and $U < P$ is the adopted number of eigenvalues, allowing for acceptable lossy reconstruction of the original information.

Rebuilded matrix, after the rejection of minor components has a form:

$$\mathbf{S}' = \mathbf{S}\mathbf{w}' \tag{3}$$

where: **w**' is a matrix made up of U successive eigenvectors.

In this case, we have a large variance of data, so we need to find such a linear combination of original data that shows the smallest variability (associated with the principal component with the smallest share in the resource information - $\min(\lambda_i)$ where i = 1,2, ... P). This follows from the fact that the observed data is to be sensitive only to change of the technical condition, and in previously analyzed data there were no such a change. The principal component can be expressed as:

$$\mathbf{S}' = \mathbf{S}\mathbf{w}_P\,. \tag{4}$$

It cannot be assumed that such a linear combination of the original data will be useful diagnostically in the monitoring system, but it is worth at this stage of research to take such a method into consideration. It can be assumed with a certainty that with the change in measurement values, at fixed initial values of the proposed coefficients, also a linear combination of the values of these measures will noticeably change.

From a practical point of view, for each track section we should determine the eigenvector of the covariance matrix of the original symptoms of a good vehicle state, corresponding to the smallest eigenvalue. Then, in order to determine the technical state changes over time, the same vector should be used to calculate the current value of the linear combination of symptoms. With examples related to different technical states, we can finally find the critical value of a so constructed replacement symptom.

Fig. 6 shows the principal component with the smallest variance, obtained from the original data (without any selection) and the principal component with the smallest variance after data rejection the method including the Chauvenet criterion (rejection of data that strongly deviate from the mean value).

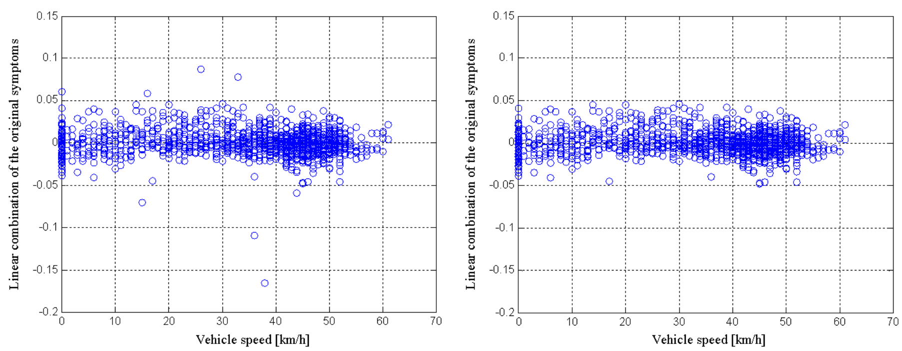

Figure 6. Principal component with the smallest variance before and after non-standard data rejection.

As shown in figure above, we finally get generalized measure with low dispersion. It should be noted that the results presented in Fig. 6 relates to the data without any selection and applies to all registered passages, vehicle speed, load, etc.. The proposed measure is in general not sensitive to changes of the vehicle speed. It is hoped that technical state changes will modify the mean value of such a measure, or its "shape" depending on the speed.

Another concept to improve data quality is the direct elimination of the speed impact on the measured symptoms. This can be done by building a model of this dependence. Assuming that: values of a given measure should oscillate around a constant value (technical state of the suspension did not change during this experiment), the speed impact is dominant and that the speed influences measured values additively, we can get rid of that dependency as follows:

$$S' = S - f(V), \tag{5}$$

where: S' – is the value of the selected measure after processing, S – initial value of the selected measure and f(V) approximative model, reflecting the speed impact on the value of S.

It was assumed that in all cases, we can use a following deterministic model:

$$f(v) = ae^{bv^2} + cv^2 + dv, \tag{6}$$

where: a,b,c,d – model coefficients estimated by the least squares method

The first component ensures the elimination of even some very rapid increases of f(v). Others allow the modeling of less rapid change. During the fit of the model, some factors may be close to zero, which eliminates a contribution of a given component in the model. Since the model is nonlinear and cannot be reduced to linear, it is necessary to use numerical methods for the estimation of parameters. For the purposes of the described preliminary study, the search of the minimum of the error function was done using the Nelder-Mead method (to find the initial estimation of parameters) and then the Gauss-Newton gradient method (to make values more accurate). It should be noted that the removal of non-stationarity of the data allows (in the next stage) the elimination of abnormal data, significantly different from the average value. An example of such a model fitted to the data is shown in Fig. 7

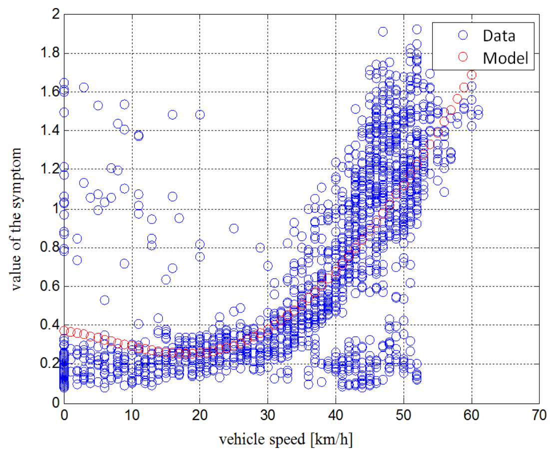

Figure 7. The proposed model fitted to the RMS acceleration value for all tramway passages on a given track section.

Figure 8 shows the standard deviation for the original observation, and observation after removal of the additive dependence of speed, and the rejection of non-standard data. The analysis shows that by the proposed method we can significantly improve data quality, even much more than by simple selection based on the vehicle speed and position (Fig. 5).

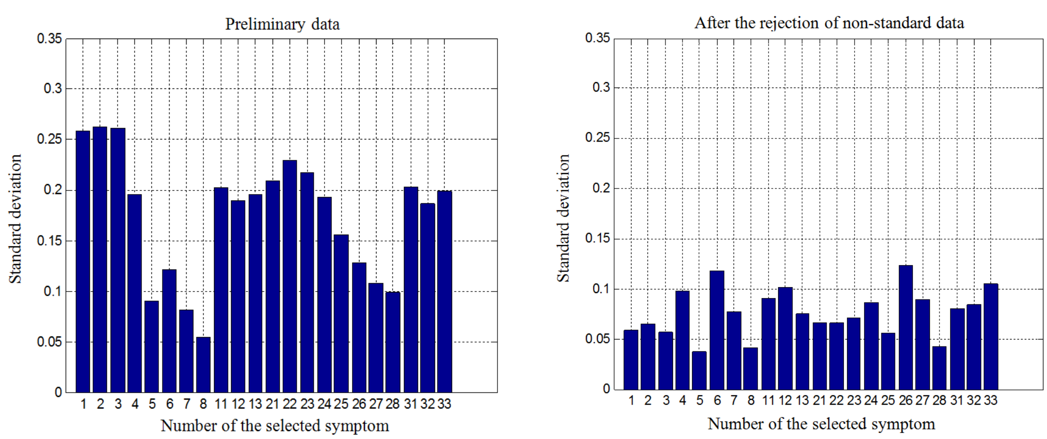

Figure 8. Evaluation of data quality before and after the removal of the trend from data.

To apply this method in practice it is necessary to determine the coefficients of the model for each vehicle state.

SUMMARY

All performed simulation and experiments serve to create preliminary assumptions for the methodology of the fault detection for a light rail vehicle suspension condition monitoring system. As a result of the primary data analysis the main factor affecting adversely the measurements is the strong speed dependence of the measured signal. However, even after taking this dependence into account, we can see an important influence of other factors, which at this stage are difficult to identify. Because it is difficult to find the unequivocal cause of differences in successive realizations (runs), all data should be considered together.

It has been shown that in order to extract the essential information contained in the data, we can apply a simple data selection in function of a track section (without starting and braking phases) and speed of the vehicle.

Another method is to use an approximative model describing the dependence of the registered measure from the speed and remove this dependence from the data. As before, this procedure reduces the variance of the data. Any potential changes in the technical condition should be revealed in the change of the mean symptom or in his image (depending on speed). The last proposition, the most promising, is associated with limitation of the measurements bandwidth and focusing only on the phenomena associated with the dynamics of body motion.

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