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# THE SELECTION PROCEDURE OF DIAGNOSTIC INDICATOR OF SUSPENSION FAULT MODES FOR THE RAIL VEHICLES MONITORING SYSTEM

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## ABSTRACT

The monitoring system of a rail vehicle and track has been developed under the project *MONIT – Monitoring of Technical State of Construction and Evaluation of its Lifespan*. The main subsystem of a rail vehicle being the object of on-line monitoring is the suspension. The principle of operation of the monitoring system is based on the statistical analysis of acceleration signals. The selection procedure of damage-sensitive parameters of signals is introduced. In order to improve suspension condition assessment, selected parameters are analysed in multidimensional space. As a result, a new diagnostic indicator is analysed – Euclidean metric between reference point (nominal state) and a point representing current measurement (condition). The proposed fault detection method was used for analysis of recorded data during an experiment on wagons with suspension damages.

**KEYWORDS :** *rail vehicle, suspension, signal analysis, condition monitoring.*

## 1 INTRODUCTION

The arising requirements for rail transport safety in recent years stimulate development of new methods and techniques of monitoring. Special attention should be paid to rail vehicles' running gear and suspension. The task of these subsystems is to provide proper running behaviour and comfort. Deterioration or damages of its elements may lead to accelerated wear of wheel profile, loss of vehicle's stability or even derailment.

Suspension has not been an aim of the monitoring since development and spread of the on-board diagnostic systems. The reason for this situation is the lack of efficient method of damage detection due to the complex relations between excitations and vehicle's dynamic response.

In order to deal with the problem of suspension condition monitoring and its damage detection, the monitoring system has been developed within the framework of '*MONIT – Monitoring of Technical State of Construction and Evaluation of its Lifespan*' project. The system is a universal solution which is applicable to practically all types of rolling stock: locomotives, wagons, multiple units. The monitoring operation of the system is also extended to track condition, axle box temperature and vehicle positioning.

The paper focuses on the functionality of the system related only to vehicle condition monitoring. A new concept of suspension damage detection method is introduced with the procedure of diagnostic parameters selection.

## 2 DAMAGE DETECTION METHOD FOR MONITORING SYSTEM

Rail vehicle's suspension is complex and generally is split, in most of modern rolling stock, into primary and secondary suspension. Primary suspension links wheelsets with bogie frame, while secondary suspension connects bogie frames with vehicle's body. Both primary and secondary suspension consists of numerous damping and spring elements, often of nonlinear characteristics. The possible faults of these elements may include: broken springs, leaking dampers, worn rubber-

metal elements, etc. All the suspension damages generally lead to decrease or increase of nominal parameters' values: damping and stiffness coefficients. Any deviations from nominal (projected) characteristics of suspension influence vehicle's dynamic behaviour and hence they are reflected in acceleration signals recorded on a vehicle relative to nominal state of the vehicle.

The assessment of rail vehicles dynamics, by means of acceleration signals analysis is used in homologation processes. An approach to suspension condition monitoring is derived from the rail standards: EN 14363 [1] and UIC 518 [2] which concern to dynamical test of rolling stock for homologation purpose. Dynamic abilities are assessed by analysing acceleration signals recorded in specific points of the vehicle. Signals measures: RMS and maximal value are compared with reference ones.

This concept of assessment can be transferred to condition monitoring field. Any deviations from nominal (projected) parameters of suspension influence vehicle's behaviour and hence they are reflected in acceleration signals recorded on a vehicle.

The simple comparison of parameters' values with the limit ones enables to detect damages that cause increase of signal's amplitude. In case of the amplitude value decrease which may occur in case of stiffness reduction caused e.g. by one broken spring, this comparison will show no damage. This problem of false assessment may be reduced to some degree by calculation of difference or distance (metric) between magnitudes. The results of previous analyses of numerical and experimental data [3, 4] led to conclusion that it is suggested to use a set of parameters characterizing acceleration signals. The changes of parameters' values may be different under the same damage and excitation – some parameters indicate faults more clearly than others [5]. In order to analyse more than one parameter a method based on multidimensional space can be implemented. The points in such a space are defined by coordinates which values correspond to each parameter value. The idea of the presented approach is to assess distance between specific points, described below.

The reference point  $S(1)$ , from which distance  $d$  is calculated, represents nominal (undamaged) state of vehicle.

$$S^v = (x_{S1}^v, x_{S2}^v, \dots, x_{Sn}^v) \quad (1)$$

where,

$x_{S1}^v, x_{S2}^v, \dots, x_{Sn}^v$  – the following coordinates values from 1 to  $n$  for the reference point and vehicle velocity  $v$ .

The point obtained after measurement and representing current condition is denoted as  $U(2)$

$$U_j^v = (x_{U1,j}^v, x_{U2,j}^v, \dots, x_{Un,j}^v) \quad (2)$$

where,

$j$  – the number of measurement,

$x_{U1,j}^v, x_{U2,j}^v, \dots, x_{Un,j}^v$  – the following values of parameters from 1 to  $n$  and vehicle velocity  $v$ .

It is essential to calculate distance between points obtained for the same velocity  $v$  and track section of congenial quality and geometry. The dynamics of a rail vehicle cannot be analyzed separately without considering track. Vehicle and track form a rail vehicle-track system, since between those two subsystems dynamic feedbacks occur. The dynamic responses of the vehicle (e. g. vibrations) depend strongly on track geometry and rail irregularities. The influence of suspension damage on recorded acceleration signals may be in some circumstances masked by the influence of track. It is important to carry out diagnostic inference on track sections of known quality and geometry. For this purpose the monitoring system is equipped with GPS module to monitor current position of the vehicle.

Statistical parameters (indicators) may have different values (scales), therefore data used for condition assessment must be normalized. Coordinates' values of current  $U_j^v$  and reference point  $S^v$  are divided by corresponding values of the reference point. After this computation  $S^v$  coordinates are (1, 1, 1).

The comparison of metrics  $d$  between points  $S$  and  $U$  is the principle of diagnostic inference. The limit value of the distance  $d$  is denoted as  $F$ . Formula (3) is the essence of the presented fault detection method:

$$\begin{aligned} d(S^v, U_j^v) &\leq F \text{ no damage} \\ d(S^v, U_j^v) &> F \text{ damage} \end{aligned} \quad (3)$$

A method of establishing  $F$  value is described in chapter 4.

### 3 DIAGNOSTIC INDICATOR SELECTION PROCEDURE

The problem of diagnostic indicator (parameters, features) selection may be solved by means of dimensionality reduction methods [6, 7]. Dimensionality reduction is a transformation of multidimensional data in order to obtain minimal number of features indispensable for characterisation of the process [8]. Methods of dimensionality reduction are represented by the two main groups:

- feature selection [9], [10],
- feature extraction [11], [12].

The first group of methods enables to select from large number of features only these ones which carry substantial information. An example of such methods is e.g. sequential forward/backward selection [10], [13],

Feature extraction methods transform current features into linear combination to reduce dimensionality and obtain a new data source. The most known method of feature extraction is principal component analysis, (PCA) [14].

The above methods can be implemented for data which directly deliver information. The problem of diagnostic indicator selection requires criterion which can associate 'damage-sensitivity' with respect to the increase/decrease of parameters vales caused by different suspension damages. The damage-sensitivity may be expressed as substantial difference between signal parameter values of nominal and damaged vehicle. This, in turn, entails greater metric  $d$  of fault detection method and facilitates condition assessment. The criterion of diagnostic indicators selection is then formulated regarding maximization of distance  $d$  and denoted  $d-max$  (4):

$$d(S^v, U_j^v) \rightarrow \max \quad (4)$$

The initial set of parameters consists of measures widely use in vibration analysis and in other forms of fault detection fields:

- RMS,
- signal energy,
- variance,
- interquartile range (IQR),
- zero-peak,
- peak-peak,
- crest factor,
- clearance coefficient,
- kurtosis.

Input data for selection process were obtained from simulation carried out in MSC.ADAMS environment. Damages introduced in a typical passenger wagon model were:

- 50% stiffness reduction of one primary suspension spring,
- 100% damping reduction of secondary suspension damper.

The simulations were performed for different scenarios which vary according to:

- vehicle velocity 60 – 160 km/h,
- track geometry: tangent, curve R=900 m,
- track quality defined by geometrical rail irregularities: QN1 (good), QN3 (poor) according to [2].

Acceleration signals were obtained from specific points of vehicle. For primary suspension condition, signals are recorded in point located on bogie frame, above wheel. In case of secondary suspension, acceleration signals are recorded on a body, above bogie center.

The number of diagnostic indicators (parameters) was chosen *a priori* in three variants:  $n = 2$ ,  $n = 3$ ,  $n = 4$ . It was assumed that number should be less than half (4 or 5) of the initial set. The sets of  $n$  elements which were generated contain all possible combination of parameters without repetition. Scheme of selection algorithm is depicted in Figure 1.

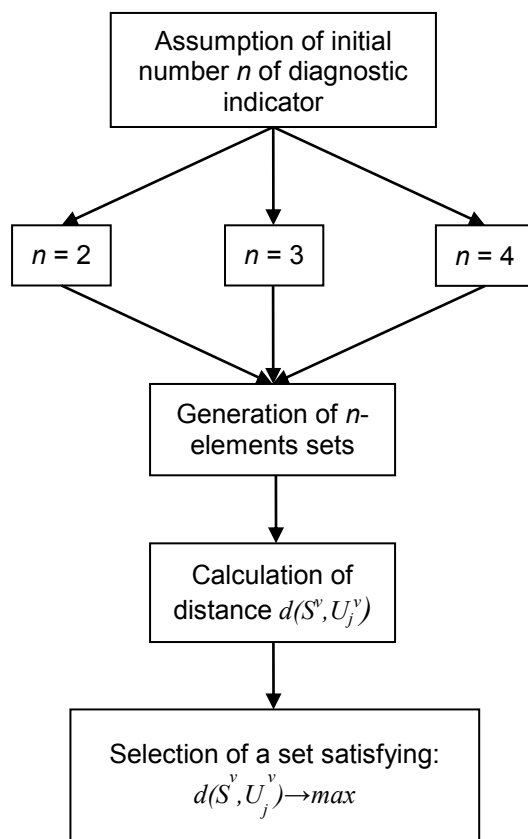


Figure 1: Diagram of diagnostic indicators selection procedure

For further analysis, sets satisfying criterion (4) are taken into consideration. Exemplary results of the selection according to algorithm are shown in table 1. Detailed repetition of indicators occurring in four-element selected sets is presented in table 2 for stiffness reduction and acceleration signal recorded for vertical (Z) vibrations of the bogie. The nominal geometry and track does not influence the much content of the resultant sets, what is indicated by high correlation coefficients. The distribution of indicators relative to track quality is also congenial. Due to these facts, the analysis can be limited only to consideration of suspension damage location and number  $n$ .

Table 1: Exemplary results of sets selection in case of primary stiffness reduction. P# – parameter (indicator). (ERG - energy, VAR - variance, CCF - clearance coefficient, ZP - zero-peak, PP - peak-peak)

Number $n$	$v$ [km/h]	$d$	P1	P2		
$n = 2$	100	0.407	ERG	VAR		
	120	0.360	ERG	VAR		
	140	0.355	ERG	VAR		
Number $n$	$v$	$d$	P1	P2	P3	
$n = 3$	100	0.479	ERG	VAR	ZP	
	120	0.411	ERG	VAR	ZP	
	140	0.416	ERG	VAR	PP	
Number $n$	$v$	$d$	P1	P2	P3	P4
$n = 4$	100	0.511	ERG	VAR	ZP	CCF
	120	0.4391	ERG	VAR	ZP	CCF
	140	0.448	ERG	IQR	VAR	PP

Table 2: Number repetition of indicators for three-elements sets in case of secondary damping reduction – acceleration signals for Z direction.

Parametr	QN1		QN3		Total	
	Tangent	Curve	Tangent	Curve		
RMS	1	1	1	0	3	3.6%
ERG	5	5	5	4	19	22.6%
IQR	1	1	1	1	4	4.8%
VAR	6	5	4	4	19	22.6%
ZP	4	4	4	5	17	20.2%
PP	3	1	4	4	12	14.3%
CREST	0	0	0	1	1	1.2%
LUZ	2	3	1	1	7	8.3%
KURT	2	0	0	0	2	2.4%
Correlation	0.875		0.937			

On the basis of the sets selection, it is possible to perform final arrangement of the indicators. For this purpose, the percentage of parameters repetition for primary and secondary suspension assessment is shown in table 3. The parameters of the greatest share are: signal energy, variance, zero-peak, peak-peak.

Table 3: Percentage shares of indicators relative to suspension.

Indicator	Primary	Secondary
RMS	3.4%	2.6%
ERG	27.2%	20.1%
IQR	3.2%	3.2%
VAR	28.3%	19.8%
ZP	15.6%	13.2%
PP	11.1%	18.0%
CREST	2.6%	6.1%
LUZ	5.8%	6.3%
KURT	2.6%	10.6%

Signal energy and variance are strongly correlated since both indicators may be considered as dispersion measures. Instead of variance which is resultant from selection, another indicator can be proposed. Table 4 contains matrix of correlation coefficients in case of damaged primary suspension (simulation model). The measures that are not highly correlated: crest factor, clearance coefficient and kurtosis are difficult to interpret in the context of railway vehicle dynamics. Consequently, a less-correlated with variance dispersion parameter should be used. Interquartile range is defined as a difference between upper and lower quartile – such calculation rejects very low and very high values which are caused e.g. by measurement errors. Expedient feature of IQR allows placing it in the final set instead of variance. For fault detection, a set of the following indicators is created:

- signal energy,
- IQR,
- zero-peak/peak-peak (primary/secondary suspension).

Table 4: Correlation matrix of acceleration signals parameters in case of primary stiffness reduction, Z direction.

	RMS	ERG	IQR	VAR	ZP	PP	CREST	LUZ	KURT
RMS	1								
ERG	0.983	1							
IQR	0.999	0.976	1						
VAR	0.982	1	0.975	1					
ZP	0.994	0.987	0.991	0.986	1				
PP	0.995	0.991	0.992	0.990	0.996	1			
CREST	-0.585	-0.468	-0.608	-0.466	-0.501	-0.534	1		
LUZ	-0.585	-0.441	-0.612	-0.439	-0.512	-0.518	0.951	1	
KURT	-0.581	-0.450	-0.607	-0.448	-0.505	-0.528	0.988	0.973	1

#### 4 APPLICATION OF FAULT DETECTION METHOD IN EXPERIMENTAL DATA ANALYSIS

A prototype of the rail vehicle and track monitoring system was used during experimental study on influence of suspension damages on recorded acceleration signals. The experiment took place on a test track in Żmigród. Two wagons were used for the study: passenger and goods wagon (coal wagon). Damages of suspension corresponded to damages studied in simulation software. Stiffness reduction was done by removing one packet of coaxial springs of Y25 bogie of goods wagon at one wheel, on left side of axle box. Disconnection of one secondary suspension damper of passenger car led to damping reduction.

The limit values  $F$  were calculated using data obtained from wagons in nominal condition. At first, the mean values of coordinates (reference points) for each experimental scenario were calculated. Then the distances  $d$  from this reference point to the points referring to nominal state were computed. The  $F$  is equal to mean value of  $d$  and two standard deviations of  $d$ . Results of damping reduction are depicted in Figure 2. The data was recorded at  $v = 100$  km/h on curve section of radius  $R = 900$  for acceleration of lateral motion of the body. Location of points is related with vehicle condition. The red points located beyond the sphere of radius  $F = 0.358$  indicate occurrence of damage. The reference point is shown as blue star in center of the sphere. It was possible in this case to detect damage basing on all four measurements.

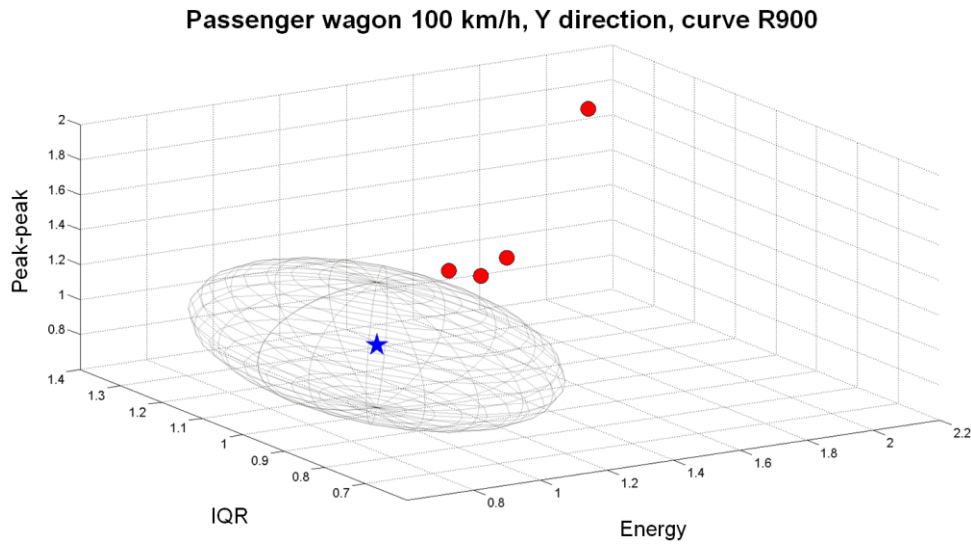


Figure 2: Experimental results for damaged passenger wagon  $v = 100$  km/h, lateral direction, curved track section  $R = 900$  m,  $F = 0.358$

An illustration of stiffness reduction analysis is shown in Figure 3 which refers to passage at  $v = 80$  km/h on curve section.

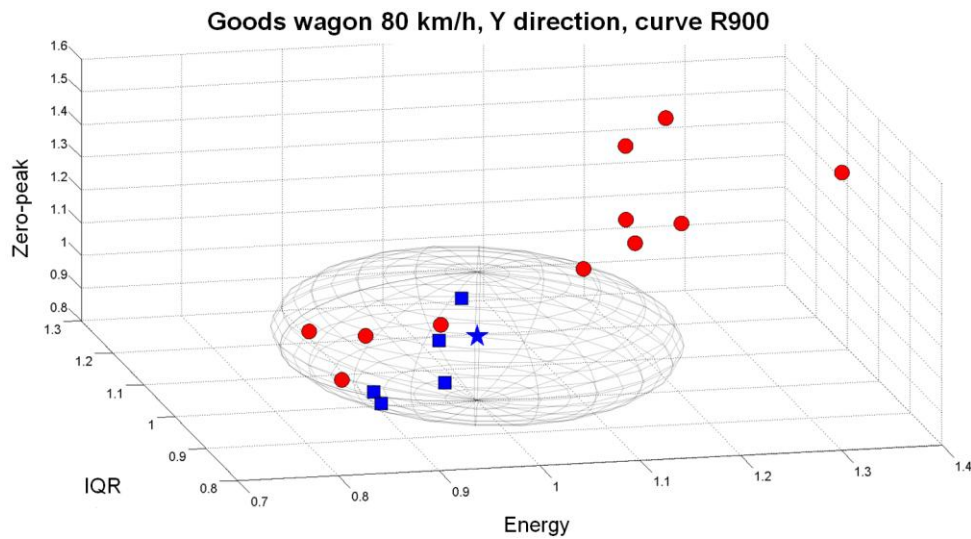


Figure 3: Experimental results for damaged goods wagon,  $v = 80$  km/h, lateral direction, curved track section  $R = 900$ m,  $F = 0.196$

The signals were recorded for vibrations in lateral (Y) direction, in point on bogie frame, above the wheel. There are many more points than in Figure 2 since more samples have been recorded in this case. Not all measurements delivered sufficient information to assess properly vehicle condition (blue squares inside sphere), nevertheless majority of the points clearly indicate fault.

**CONCLUSION**

The presented selection procedure of diagnostic indicators is of a heuristic nature. The dynamic changes of rail vehicle response for various suspension damages are difficult to categorize and



direct interpretation. An approach to the selection process required consideration of fault detection method. The definition of selection criterion is intended to maximize distance between reference point (nominal vehicle) and point representing damaged state. Among obtained sets of indicators it was possible to select these ones which repeated in sets the most frequently. There has been change in the final set of indicators, since interquartile range was chosen instead of variance.

The fault detection method for the rail vehicle monitoring system enables to detect fault of different kind in the suspension system. The selected indicators are ‘damage-sensitive’, but it is necessary to assess suspension condition taking into consideration more samples.

## REFERENCES

- [1] UIC 518. *Testing and approval of railway vehicles from the point of view of their dynamic behaviour - Safety - Track fatigue - Ride quality*, 4-2009.
- [2] EN 14363. *Railway applications - Testing for the acceptance of running characteristics of railway vehicles - Testing of running behaviour and stationary tests*. 2007.
- [3] A. Chudzikiewicz, B. Sowiński, A. Szulczyk. Statistical parameters of vibrations as measures of rail vehicle condition, *17th International Congress on Sound and Vibration*, Cairo, Egypt 18–22 July 2010, p. 73.
- [4] A. Chudzikiewicz, B. Sowiński. Simulation Method of Selection of Diagnostic Parameters in the Process of Monitoring the Rail Vehicle's Conditions, *Structural Health Monitoring 2011: Condition-Based Maintenance and Intelligent Structures*, Book Series: Structural Health Monitoring (SHM). Vol. 1, 2011, pp. 1103–1110.
- [5] R. Melnik, M. Kostrzewski. Rail Vehicle's Suspension Monitoring System - Analysis Of Results Obtained From Tests Of The Prototype, *Key Engineering Materials* Vol. 518, 2012, pp 281–288. DOI: 10.4028/www.scientific.net/KEM.518.281
- [6] Y. Ma., L. Zhu L. A Review on Dimension Reduction, *International Statistical Review*, Volume 81, Issue 1, April 2013, pp. 134–150. DOI: 10.1111/j.1751-5823.2012.00182.x
- [7] P. Cunningham. *Dimension Reduction*. University College Dublin, Technical Report UCD-CSI-2007-7, 2007.
- [8] L. van der Maaten, E. Postma, J. van den Herik. *Dimensionality Reduction: A Comparative Review*. Tilburg centre for Creative Computing, Tilburg University, 26 October, 2009.
- [9] M. Dash, H. Liu. Feature Selection for Classification, *Intelligent Data Analysis 1* Issues 1–4, 1997, pp. 131–156
- [10] I. Guyon. An Introduction to Variable and Feature Selection, *Journal of Machine Learning Research 3*, 2003, pp. 1157–1182.
- [11] H. Almuallin, T.G. Dietterich. Efficient algorithms for identifying relevant features, *Proc. of 9th Canadian Conference on Artificial Intelligence*, Vancouver BC, 1992, pp. 38–45.
- [12] H. Liu, H. Motoda. *Feature extraction for knowledge discovery and data mining*. Springer Verlag, 1998. ISBN:079238198X
- [13] A. Marciano-Cedeño, J. Quintanilla-Domínguez, M.G. Cortina-Januchs, D. Andina. Feature Selection Using Sequential Forward Selection and classification applying Artificial Metaplasticity Neural Network, *IECON 2010 - 36th Annual Conference on IEEE Industrial Electronics Society*, 7–10 Nov. 2010, Glendale, AZ, USA, pp. 2845–2850, DOI: 10.1109/IECON.2010.5675075
- [14] Y. Tharrault, G. Mourrot, J. Ragot, D. Maquin. Fault Detection and Isolation with Robust Principal Component Analysis, *Int. J. Appl. Math. Comput. Sci.*, Vol. 18, No. 4, 2008, pp. 429–442. DOI: 10.2478/v10006-008-0038-3

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