THE INVESTIGATION OF THE TECHNICAL CONDITION OF RAILWAY SYSTEMS

Bogdan Zółtowski

University of Technology and Life Sciences in Bydgoszcz
Faculty of Mechanical Engineering
Prof. Kaliskiego Av. 7, 85-796 Bydgoszcz, Poland
tel.: +48 52 3408286, fax: +48 52 3408286
e-mail: bogzol@utp.edu.pl

Abstract

The multidimensional monitoring of symptoms applied to railway systems allow to detect and locate the sections of the track (straight and curved) that generate the decrement of the safety and comfort of the passengers. It also evaluates the technical state of the rail-vehicle interface. In addition, it allows observing, evaluating, and controlling the reliability and availability of the system.

The objective of the study is to propose an alternative to evaluate the condition of the technical state of railway systems from a dynamical point of view that guarantees the safety and comfort of the passengers. One looks for diminishing the operative costs of maintenance, improving the use of equipment for tasks of maintenance for the track, vehicle and auxiliary equipment, optimizing the time of the maintenance personal, the maintenance frequencies (corrective, preventive, etc.). It also aims to identify the variables related to maintenance actions that have a high influence on the technical state of the system.

This paper presents the results obtained when applying a modelling of this type to a railway system, being cantered mainly in the application of SVD theory to the technical diagnosis of systems.

Keywords*: Multidimensional Monitoring of Condition (MMC), Singular Value Decomposition (SVD), Railway Technical Diagnosis*

1. Introduction

Technical systems are becoming more complex when talking about their mechanic, and electronic. Technologic advances tend to be more auto sufficient and able to auto diagnose themselves, what allow determining if any anomaly is present in any subsystem, or component, to finally decide whether the system must or not be stopped.

The conventional maintenance with some factors such as the lack of communication between dependencies, a not proper management of information, not having a clear monitoring policy nor variables trends among other, do not allow the performance of an integrated diagnose of the system.

Due to the previous factors, it is necessary to implement new methodologies of technical diagnostic, in order to satisfy all of the company's needs, getting as result, an integrated diagnose through computing simulation, tools, analysis methods and information evaluation from the machine's technical state.

The multidimensional monitoring of symptoms – MMC – has been developed as an alternative that fits the new technology demands, it assures the obtain of performance indicators such as the reliability before any damage within the system, giving as a result less critical failures, unexpected pauses of production, dead times, maintenance costs, and the mistreatment of human resources, among others.

The holistic approximation presented in the previous figure, obtains the information about the dynamic system operation, and the maintaining activity history through:

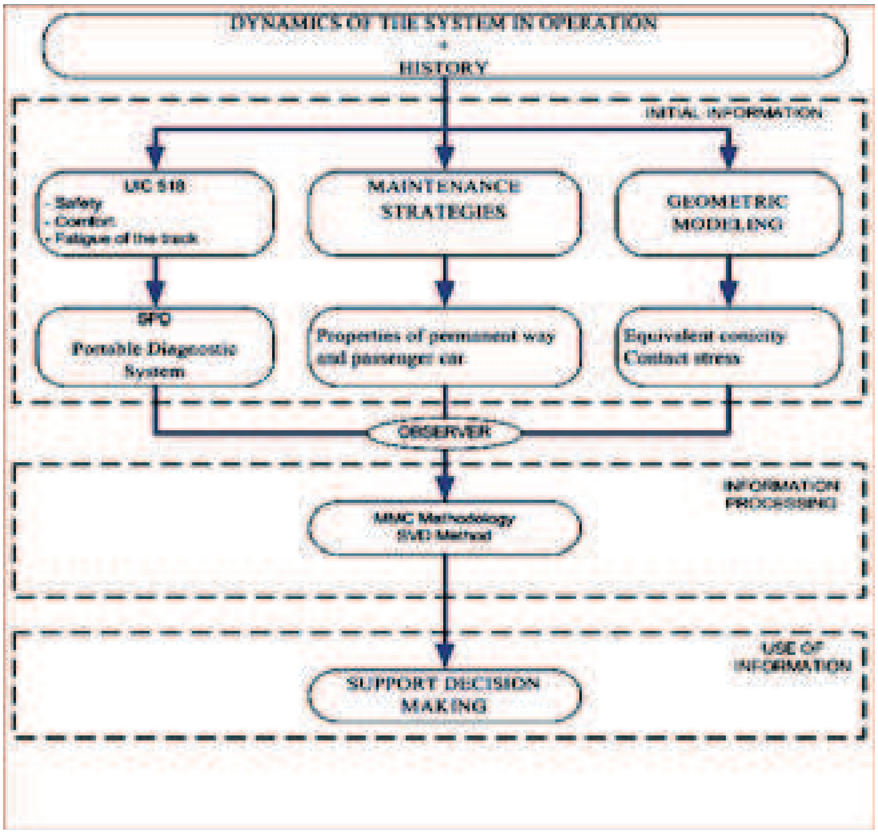

Fig. 1. Diagnose model with a holistic approximation for the railways systems

– the portable diagnose system (PDS), which registers acceleration and force signals in order to evaluate the security, comfort, and railways fatigue according the International Law UIC518 (Tests and approval of rail vehicles from the point of view of their dynamic behavior, safety, railway wear and quality of the travel (comfort)),
– the managing strategies of the company, taking into account the permanent way and vehicle variables,
– a geometric modelling of the wheel – rail interface, through which is possible to obtain the equivalent iconicity, and the contact efforts, which are the factors that describe the relation mentioned above,
– the holistic approximation, bases on the application of MMC methodology, which is based on the singular values decomposition method (SVD) as well. SVD determines the general failure of the system, which is the indicator of the integral technical state of the system. Its evaluation allows the improvement of the actual management actions, and the rise in the availability, reliability, and maintainability indicators of the technical system.

2. Multidimensional monitoring of condition

Figure 2 shows the followed methodology for this study case, 4 main groups are warned, in the first one, the energy processors theory is reflected, where through the exit energy study, the technical state of the system , and its deterioration can be inferred. First, a signals processing (second group) must be done due to the fact that phenomena's like vibration, noise and heat can be measured by data acquisition equipment, and instrumentation (symptom monitoring).

At this point, it is important to establish what kind of measuring points of the physical variables are appropriate in order to obtain relevant information, that is why a selection of measuring points will be made to establish the point generating the higher amount of information, and the lower amount of useless information about the technical state of the system.

Fig. 2. Methodology for a holistic approximation

Once the measuring points are established, the monitoring of the physical variables can be made, assuring relevant information about the system. Acquired signals are then transformed into a symptom series. The calculation parameters of these symptoms might be obtained by any norm alignment, or by a temporal series statistic analysis, in which basic statistic scalars can be calculated, as the half, standard deviation, bias, form factor, clearance factor, among many others. Way much complex analysis like the spectral, the insolvent, the spectral, frequency time, cycle stationary and superior order statistic analysis might also be developed in order to obtain symptoms that reflect the measuring signal. For the present study, the signal processing is being done through SPD.

A third group within the methodology is composed by the technical system's proper information, like system operation variables, system parameters, and a technical system geometric modulation. Among those sources of information, a series of periodically measured variables can be found.

To perform a multidimensional monitoring is necessary as a first step, to determine the symptom observation matrix, which is composed of the symptoms in its columns and the measures of those symptoms in its rows. This matrix contains information about the system's technical state and the proposed methodology seeks to extract the relevant information.

The observation matrix is reduced through a Principal Component Analysis PCA, which along with a series of reduction criteria allows identifying the symptoms containing relevant information about the system's technical state.

Based on the reduced matrix (space of reduced symptoms) and by using the Singular Value Decompositions SVD, the general failure that presents the evolution of the system's technical state is determined. It is a variable that consolidates the information about the system's technical state, contained in principle in the symptom observation matrix.

Once the general failure and its limit value have been determined (through statistical methods), it is possible to perform an integral diagnostic of the system by estimating the conditions under which the general failure exceeds its limit value. Forecasting tasks can be made beginning with the general failure in order to predict the future technical state of the system. It is also possible to create indicators of the system's technical state from the general failure, such as the functions of risk and reliability, which support the system diagnostic. And finally, it is possible to establish general models (through multiple linear regression) that describe the behaviour of the general failure in order to enter current, future, real or assumed values to the model and so determine their influence over the general failure.

3. SVD General Theory

The symptoms observation matrix defined by $O_{pr} \in \Re^{r \times p}$ is an array of symptoms at certain moments of the life of the technical device θ. It can be said that the symptoms observation matrix is a discrete way of observing symptoms (Cempel, 2000, p. 2).

The aim of obtaining a symptoms observation matrix O_{pr} is to obtain all the information related to the condition of state of the technical system and to distinguish different forms of failure that evolve during its operation (Cempel, 2000, p. 2). The symptoms observation matrix of a system is represented as follows (Natke-Cempel, 2001, p. 599):

$$O_{pr} = \{S_{ij}\} = \left.\begin{array}{c} \overbrace{\phantom{S_{1,1} \quad S_{1,2} \quad \cdots \quad S_{1,j} \quad \cdots \quad S_{1,r}}}^{\substack{\textit{Variable} \\ \textit{Symptoms}}} \\ \begin{bmatrix} S_{1,1} & S_{1,2} & \cdots & S_{1,j} & \cdots & S_{1,r} \\ S_{2,1} & S_{2,2} & \cdots & S_{2,j} & \cdots & S_{2,r} \\ \vdots & \vdots & \ddots & \vdots & & \vdots \\ S_{i,1} & S_{i,2} & \cdots & S_{i,j} & \cdots & S_{i,r} \\ \vdots & \vdots & & \vdots & \ddots & \vdots \\ S_{p,1} & S_{p,2} & \cdots & S_{p,j} & \cdots & S_{p,r} \end{bmatrix} \end{array} \begin{array}{c} \\ \to \theta_1 \\ \to \theta_2 \\ \vdots \\ \to \theta_i \\ \vdots \\ \to \theta_p \end{array} \right\}, \quad \begin{array}{ll} \textit{Observations} & i = 1, 2, \cdots, p, \\ \textit{Measurements} & j = 1, 2, \cdots, r, \end{array}$$

where columns $j = 1,2,\cdots,r$ are the measured symptoms and rows $i = 1,2,\cdots,p$ are the measurements made to each symptom at certain moments of the technical system's life.

In some cases, the information of several columns can be redundant and varies among symptoms contained in the matrix O_{pr}. This can be avoided by removing the correspondent (redundant) columns using tools such as the PCA.

The Singular Value Decomposition SVD is used in order to obtain different modes of failure that evolve in a system, evaluating the wear progress through indexes and indicators.

The application of the SVD to dimension the symptoms observation matrix, is expressed as follows (Bongers, 2004, p.42), (Cempel, 2000, p.4), (Cempel, 2004, p.2), (Cempel, 1999, p.179), (Cempel, 2003, p.1293), (Cempel, 2003, p.2), (Cempel, 2000, p.5), (Cempel-Tabaszewski, 2006. p.3), (Cempel-Tabaszewski, 2003. p.216), (Cempel-Tabaszewski, 2005. p.3), (Wall-Rechtsteiner-Rocha, 2003, p.2):

$$O_{pr} = U_{pp} * \sum\nolimits_{pr} * V_{rr}^{T}, \tag{1}$$

U_{pp} : is an orthogonal matrix of dimension p , of the left singular vectors,

V_{rr} : is an orthogonal matrix of dimension r , of the right singular vectors,

$\sum_{pr}$: is a diagonal matrix of the singular values:

$$\sum\nolimits_{pr} = diag(\sigma_1, \sigma_2, \cdots, \sigma_i). \tag{2}$$

The singular values σ_t, are expressed by numbers and u_t, v_t are the singular vectors representing the columns of their corresponding matrices $\sum_{pr}, U_{pp}, V_{rr}$. At the same time, these vectors are creating independent sub-matrices $(O_{pr})_t$, which totally describe the modifications of the operational system, that is; its evolution, wear or its failure modes on time $t = 1,2,\cdots,z$ (Cempel, 2003, p. 1293).

The singular values different from zero $\sigma_t > 0$ indicate failure or damage. These values are used to detect changes in the system and to evaluate their intensities. Failure intensities are organized by their magnitudes as shown in the main diagonal of the singular values of O_{pr} (Natke-Cempel, 2001, p. 610).

General failures are determined by using the singular values and vectors σ_t, u_t, v_t found through the SVD, obtaining an interpretation of the evolution of the condition of state of the technical system. These technical failures are given by (Cempel, 2000, p. 4), (Cempel, 2004, p. 2), (Cempel, 1999, p. 179), (Cempel, 2003, p. 1293), (Cempel, 2003, p. 2), (Cempel, 2000, p. 5), (Cempel-Tabaszewski, 2006. p. 3), (Cempel-Tabaszewski, 2003. p. 216), (Cempel-Tabaszewski, 2005. p. 3), (Wall-rechtsteiner-Rocha, 2003, p. 2):

$$SD_t = O_{pr} \times v_t = \sigma_t \cdot u_t, \tag{3}$$

where SD_t is the left singular value amplified by the corresponding singular value σ_t. Hence, this value has independent information in the form of failure as well as information in the intensity of these failures because of the inclusion of σ_t.

So, for a lifetime θ of the system, quantities $SD_t(\theta)$ and $\sigma_t(\theta)$ are independent of one another and help as indexes of the system changes during the operation.

From the viewpoint of energy equivalence of a norm, the following can be said: $\sigma_t(\theta)$ can be treated as an index of the wear progress (intensity), while the $SD_t(\theta)$ is the momentary form during the evolution of the condition of state of the system (Cempel, 2003, p. 1294).

One of the indexes that can be obtained through the SVD is the profile of total general failure $P(\theta)$ or $SumSD$ which represents the evolution of the general state of the technical system and is estimated as (Cempel, 2003, p. 1296), (Cempel-Tabaszewski, 2005. p. 4):

$$P(\theta) = SumSD = \sum_{i=1}^{z} |SD_i(\theta)|. \tag{4}$$

The profile of total general failure $SumSD$, will be used to describe the technical state of the system under research and from now on will be named general failure.

Through the general failure is possible to perform diagnostic and forecast tasks, as well as establishing some additional indicators of the condition of the technical system and defining state models.

4. Implementation of the multidimensional monitoring of the condition

We implement the multidimensional monitoring of symptoms in a railway system type metro and present the information sources of the system's technical state as well as the conditions considered for the implementation and the results obtained through a computational tool based on the proposed methodology.

4.1. Description of the experiment

The analysis focus on a commercial railway and it is developed for a sample of approximately 16 straight sections and 37 curved sections as well as a representative sample of passenger vehicles

(17 out of a 42 cars fleet). The related symptoms are the estimators considered by the UIC518 standard for the evaluation of security, comfort and wear of the railroad; the geometric properties of rail and vehicles as well as estimators related to the wheel-rail interface. Two groups of matrices are formed:

a) The first group is made up of the estimators calculated from the UIC518 standard $W_{i,k}$ the properties of the railroad $Y_{i,l}$ and the estimators related to the wheel-rail interface $Z_{i,j}$ (for a total of 31 estimators). There is a sample of straight sections i as observations of these symptoms. So we have 17 matrices of this type, one for each passenger vehicle analyzed.

$$O_{pr} = O_{16x32} = \begin{bmatrix} Estimators & Estimators & Estimators \\ wheel-rail & UIC & track \\ \{Z_{i,j}\} & \{W_{i,k}\} & \{Y_{i,l}\} \end{bmatrix}, \qquad \begin{array}{l} i \approx 1,2,\cdots,16, \\ j = 1,2,\cdots,5, \\ k = 2,3,4,8,9,10,13,\cdots,18, \\ l = 1,3,4,\cdots 15. \end{array}$$

b) The second group is similar to the first one but here a sample of curved sections i is considered for a total of 35 estimators. 17 matrices of this type are obtained as well.

$$O_{pr} = O_{37x35} = \begin{bmatrix} Estimators & Estimators & Estimators \\ wheel-rail & UIC & track \\ \{Z_{i,j}\} & \{W_{i,k}\} & \{Y_{i,l}\} \end{bmatrix}, \qquad \begin{array}{l} i \approx 1,2,\cdots,37, \\ j = 1,2,\cdots,5, \\ k = 1,4,6,8,9,10,11,13,\cdots,20, \\ l = 1,2,\cdots,15. \end{array}$$

To contract the matrices mentioned before, we used information obtained from maintenance employees from the company as well as from experimental measurements performed in normal operation conditions of the system.

4.2. Experiment Results

Each of the formed matrices is entered to the multidimensional monitoring of condition MMC. As a first step, they are transformed considering the mean value and the standard deviation of each of the estimators; then, they are entered in the dimensionality reduction module through the analysis in main components. Once the estimators providing little information about the technical state have been established, they are removed from the original matrix (with no transformations).

The reduced matrix is again transformed but this time with respect to the initial value of each estimator. It is entered in the singular value decomposition module SVD through which the general failure is determined. This is an indicator of the general state of the technical system whose limit value is calculated by the Neyman-Pearson method, considering an availability of $G = 0.9$ and a level of unnecessary repairs of $A = 0.1$.

Once the general failure and its correspondent limit value have been calculated for each group of matrices, a diagnostic is performed, the indicators of state are generated and its general models are proposed. We now present the obtained results for each group of matrices formed.

Figure 3 shows the general failure obtained from an observation matrix where symptoms are the variables measured on the railroad, the estimators obtained after applying the SPD and the ones calculated for the wheel-rail interface. The observation of these symptoms was made in vehicle 05 running through different curved sections of the railroad.

Axis x represents the observations obtained from the general failure (curved sections) while axis y represents the amplitude of the failure. The diagnostic is hence developed when determining the railroad section in which the general failure exceeds its limit value; section where the company should consider doing maintenance.

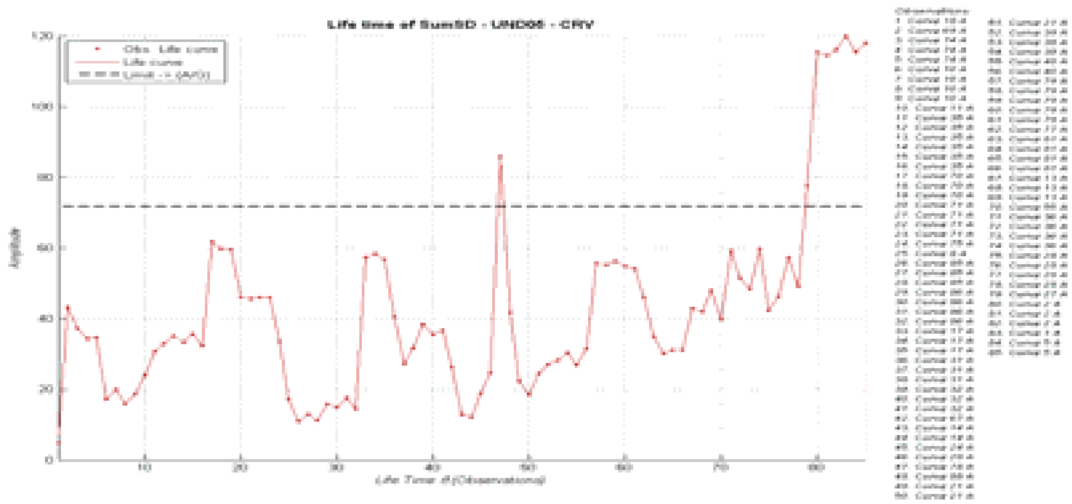

Fig. 3. Profile of the general failure

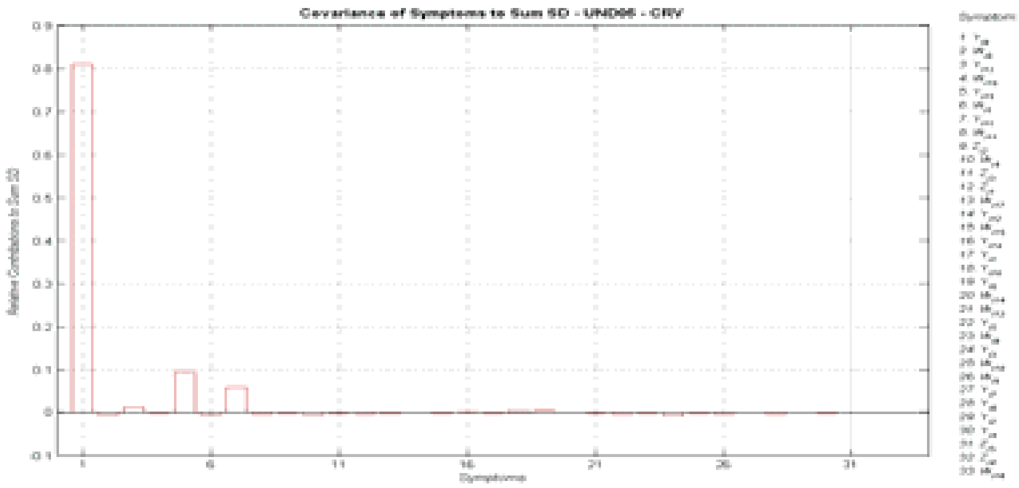

Fig. 4. Covariance of symptoms with the general failure

Figure 4 shows the covariance's (axis y) between the general failure and the symptoms considered on the analysis (axis x). Symptoms having a high relative covariance when comparing with other symptoms are assumed to be responsible for the exceeded value of the general failure (respecting to its limit value). So, once we identify the road section in which the general failure exceeds its limit value, we find through covariance's the symptom generating this condition and in this way, maintenance actions can be focused on particular road sections and on possible phenomena happening in these sections.

4.3. Results for UIC estimators, railroad properties and estimators of the wheel-rail interface for straight sections

The procedure described before is applied to the 17 matrices in which the evolution of symptoms is given by the straight sections of the railroad. In 64.7% of the cases (analyzed units), the variable representing a greater importance is the railroad corrugation, 11.8% is due to the rail corrugation and its alignment, 11.8% is due to the alignments only, a 5.9% is due to the equivalent iconicity and a 5.9% to the lateral forces. In 76.5% of the cases, the system's reliability is reduced in the straight section ENV-86. In 70.6% of the cases, reliability is reduced in the straight section 77-81. This happens because the general failure exceeds its limit value.

4.4. Results for UIC estimators, railroad properties and estimators of the wheel-rail interface for curved sections

In 41.2% of the cases (analyzed vehicles) the most relevant variable was the railroad corrugation, a 17.6% is due to the railroad corrugation and the horizontal alignment, 23.5% due to the lateral forces and 17.6% due to the quasi-static lateral accelerations. In 76.5% of the cases, the system's reliability decreases in curve 2 and in 70.6% of the cases, reliability decreases in curve 5.

4.5. Models of state for the general failure

Once the general failure and its relationship with the measured symptoms has been determined, an analysis of multiple regression is developed considering the matrix formed by the estimators of the UIC518 standard, the geometric properties of the railroad and the estimators related to the wheel-road interface, for straight and curved sections.

The general failure found after the application of the SVD is considered as a dependent variable. The most representative symptoms in each case (symptoms having a great participation on the general failure) are considered as independent variables.

Particular models for each of the 17 analyzed vehicles are determined and then, each of these models is applied to real data from the other 16 vehicles in order to obtain a general model adaptable to most of the cases.

We now present the general model obtained for the general failure *SumSD* from the straight sections of the railroad:

$$\begin{aligned} SumSD = {} & 18.74 + 24.80Y_{i,9} + 14.28Y_{i,15} - 11.36Y_{i,14} - 7.91Y_{i,10} - 5.02W_{i,18} \\ & - 4.62Y_{i,8} + 3.09W_{i,2} + 3.00Y_{i,13} + 2.49Y_{i,12} - 1.26W_{17} - 0.97Y_{i,3} - 0.44Z_{i,1} - 0.20Y_{i,11}. \end{aligned} \tag{5}$$

This model adapts with an acceptable global significance to 7 of the 17 vehicles under research (the level of significance is assumed $\alpha = 0.05$). Fig. 5 shows the three best adaptations of the general model.

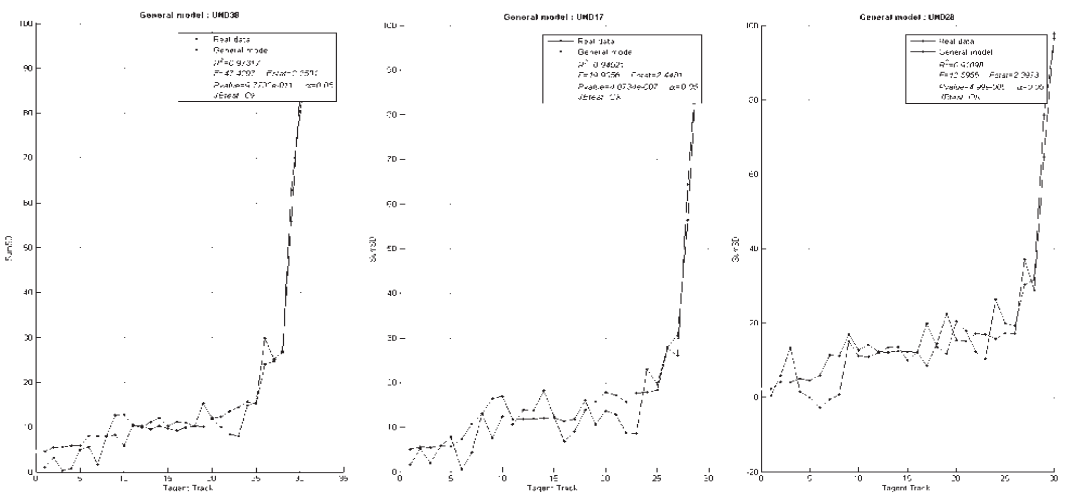

Fig. 5. A representation of the three best adaptations of the general model obtained for straight sections of the railroad

The following is the general model obtained for the general failure *SumSD* from the curved sections of the railroad:

$$\begin{aligned} SumSD = {} & 44.13 + 27.07Y_{i,9} + 8.00Y_{i,15} + 7.78Y_{i,11} + 4.30Z_{i,2} + 1.80W_{i,11} \\ & + 1.38Z_{i,1} + 0.32W_{i,4} - 0.31W_{i,1} - 0.13W_{i,6} + 0.06W_{i,18}. \end{aligned} \tag{6}$$

This model adapts with an acceptable global significance to 8 of the 17 vehicles under research (the level of significance is assumed $\alpha = 0.05$). Fig. 6 shows the three best adaptations of the general model.

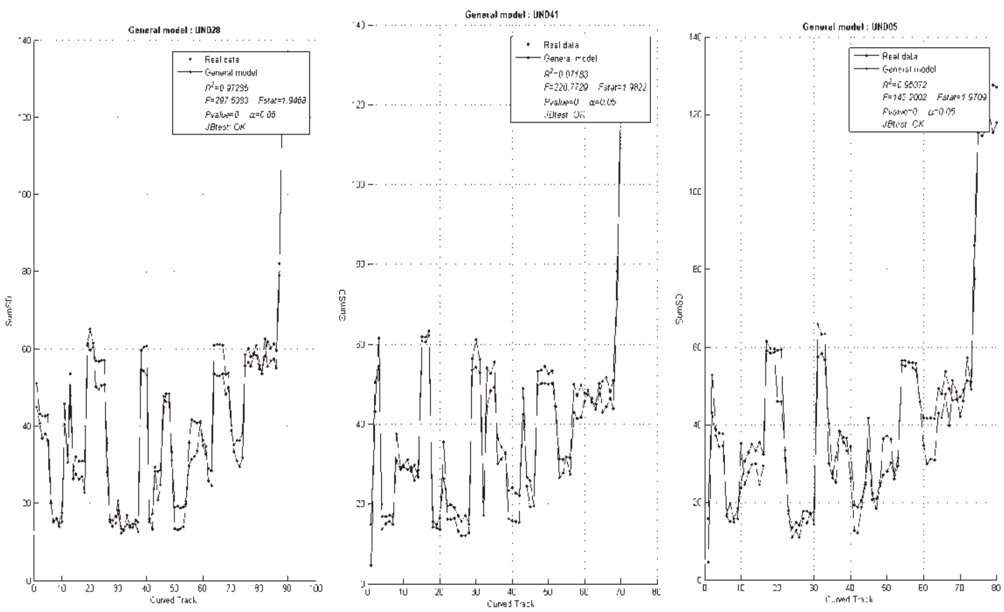

Fig. 6. A representation of the three best adaptations of the general model obtained for curved sections of the railroad

By determining these models, we pretend to establish the condition of the general failure of the system for current conditions of the geometric parameters of the rail-vehicle interface. This allows we make a rapid diagnostic of the system in order to identify the necessary actions of maintenance.

5. Conclusions

The multidimensional monitoring of symptoms help us identifying the railroad sections and vehicles needing a detailed revision by the personnel of railroad maintenance and they mobilization. It also gives us clues about what happens in the road sections under research. Hence, this type of monitoring in this specific case becomes a tool that supports in maintenance decisions which translates into a reduction in maintenance related costs, an optimal use of the maintenance personnel and additionally, it increases the availability and reliability of the system.

The research was performed under normal conditions of operation considering dynamic variables of the vehicles, estimators related with the wheel-rail interface and with parameters commonly used by the personnel of maintenance and mobilization in order to obtain information about the general technical state of the system.

Rails corrugation is the main factor affecting the reliability of the system in straight and curved sections since it influences the general failure, which let us infer about the general technical state of the system. It is also known that the railroad corrugation produces vibrations on the suspended masses of the vehicle and such vibrations are transmitted to the passengers generating them discomfort.

Other influencing factors are the lateral force measured in the axes' extremes. This force affects the stability and security of the vehicle when it travels through curved sections, as well as the railroad alignments and the quasi-static lateral accelerations measured in the vehicle's box (which measures the influence over the passengers' comfort).

Road sections generating a loss of reliability on the system are: straight section ENV-86, straight section 77-81, straight section 85-87, curve 2, curve 5, curve 4 and curve 1. So we could suggest a change in the maintenance routines in order to give priority to these road sections.

Two general models for the evaluation of the general failure in straight and curved sections were established. This was made in order to quantify the general failure in current conditions of the rail and the vehicle, supporting the maintenance activities.

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