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A New Method for Maintenance Management Employing Principal Component Analysis

Fausto Pedro García Márquez[1]

This paper presents a simple graphic method for detecting and classifying faults in point mechanisms based on the study of some statistical parameters of the force and current signals of the point machine. Principal Components Analysis (PCA) employed in order to reduce the number of these parameters. PCA is utilised in this paper for modifying the parameter dataset, and reducing the coordinate system by linear transformation. It is then possible to plot the new coordinate system in 2 or 3 dimensions, where the faults can be detected and identified. In this work most of the faults could be detected, but only a few experiments could be identified.

Key words: Principal Component Analysis, Maintenance Management, Railway Transport System, Point Mechanisms, Tournouts

1 Introduction

A train can change from one track to other only at certain places employing rail moving parts, called blades, guided by different mechanisms. These components are called point mechanisms. Point machines move the blades and it leads that the trains can change the track or not (see Figure 1). They have two possible movements: normal to reverse and reverse to normal. There are different types of point machines, but the most important are the electro-pneumatic, hydraulic and the mechanical.

The advantages of an electro-pneumatic point machines are immunity from electromagnetic interference, the large power reservoir tank and fast response. However the cost of its compressors is high and failure of the air supply pipe can cause great problems. Generally, there are also mechanical linkages for the detection and locking of the point. The standard railway point is therefore a complex device with many potential failure modes [Roberts et al. (2002)].

The electro-hydraulic point machine basically comprises an electric motor, a pump

[1] Ingenium Research Group, Universidad Castilla-La Mancha, Campus Universitario s/n, 13071 Ciudad Real, Spain. FaustoPedro.Garcia@uclm.es

and a cylinder (or various). The pump is driven by the electric motor, and generates the pressure required to move the cylinder. The cylinder can rotate completely in each operation. The throwing disk is connected to the throwing rod which moves the point. This type of point machine has the same properties as electro-pneumatic point machines [Fry (1999)].

The electro-mechanical point machine studied in this paper contains a switch actuator and a locking mechanism (see Figure 1). The mechanism is normally divided into three major subsystems [García Márquez and Schmid (2007)]:

- The motor unit which may includes a contactor control arrangement and a terminal area;
- A gearbox comprising spur-gears and a worm reduction unit with overload clutch;
- The dual control mechanism as well as a controller subsystem with motor cut-off and detection contacts.

A fault detection and diagnosis system was been developed as explained in the next section.

2 Fault detection and diagnosis

Fault detection and diagnosis (FDD) systems are a more advanced version of condition monitoring systems(CM), incorporating 'intelligent' algorithms capable of de-

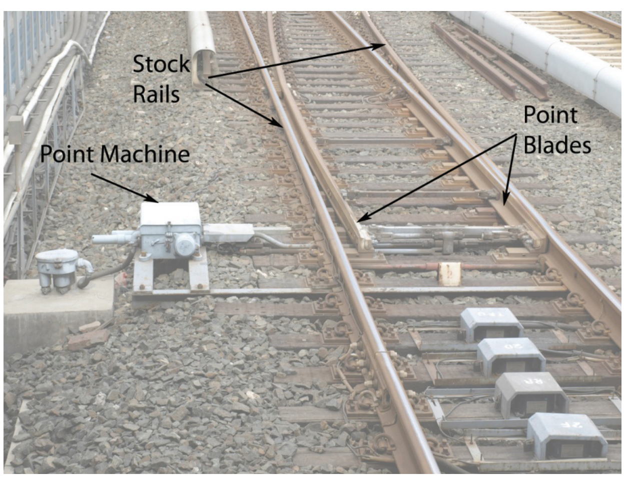

Figure 1: Main parts of a point mechanism.

tecting faults prior to failure, diagnosing the incipient fault and providing some indication of the criticality of the detected fault [Venkatasubramanian et al. (1990)].

Over recent years, researchers have developed algorithms, methods and techniques for detecting faults, the principal ones being presented in reference [García Márquez et al. (2010)]. These works lead to maintainers understanding what the CM is doing.

One of the most important objectives of using FDD is to minimize the preventive/corrective maintenance cost [García Márquez et al. (2008)]. It is also necessary to minimize the number of sensors employed in the system based on the type of mechanisms that is being analysed. The most common sensors applied in electro-mechanical point machines are current and force sensors [García Márquez et al. (2003)], [García Márquez et al. (2003)] and [McHutchon et al. (2005)], which have been employed in this work. It is also common to employ current sensors together with voltage [Zattoni (2006)], or throwing load and blade position sensors [Shimonae et al. (1991)]. Some authors have considered more sensors, for example Zhou et al. have utilised 16 different sensors measuring for example distance, motor driving force, driving current and voltage, electrical noise, temperature and state changes [Zhou et al. (2002)].

3 Experiments

The force sensor measures the stress in the operating rod of the electric point machine. The throwing load can increase due to inadequate lubrication, changes in weather or inadequate adjustment, or because of an obstacle between the point blade and stock rail [García Márquez et al. (2003)]. The current sensor measures the operating current of the induction motor installed in the electric point machine. A current signal is useful for detecting an increase in the throwing load because the operating current of any motor, including induction motors, is affected by load torque. If the current increases significantly while the force stays the same, this indicates a problem in the electric parts of the drive or in the gearbox [García Márquez et al. (2003)].

When the system does not lead to relaxation of the point by a locking system the initial and final force values in any curve are non-zero. The majority of point mechanisms, e.g., those used in most counties in Europe, do not require the provision of a drive force in the end positions [García Márquez et al. (2010)]. This type of point mechanism has been employed in this paper for the experiments.

- The faults considered in this study are listed as follows:
- Back drive overdriving at heel on normal(reverse) side with dry (lubricated)

slide chairs

- Back drive slack end off at toe end (LHS drive basket slack end off)
- Back drive tight end at heal end (RHS tight end)
- Back drive tight end at hell end (LHS tight end)
- Diode snubbing block disconnected
- Drive basket loose
- Drive rod stretcher bar loose RHS
- Dry slide chairs
- Low tension on motor brush
- Lubricated slide chairs
- Obstruction at first/second bearer on normal(reverse) side of points
- Obstruction at toe on normal(reverse) side of points
- Operational contact in original position
- Operational contact slack end off by one/two holes
- Tight lock on reverse side (Sand on all bearers on both sides)

Based on different pattern recognition and data analysis algorithms, different methods for FDD have been applied in this work. The most critical faults could be detected by clustering of statistical parameters of the current and force signals as in reference [McHutchon et al. (2005)]. The statistical parameters were: Maximum, minimum, mean, peak to peak, standard deviation, root mean square (RMS), shape factor, crest factor, impulse factor, kurtosis and definite integral. Figure 2 shows an example where ‘x’ are the trials faults listed above and ‘y’ is the parameter magnitude in the original signal. Trials 1-3 are the ‘as commissioned’ case.

The reference signals used for detecting faults depend on environmental conditions (temperature, humidity, etc.), and the mechanism conditions as the friction forces, temperature, etc. [García Márquez et al. (2010)]. In this paper the dynamic character of the electric point mechanisms has been considered. For that propose the signal analyzed in the model is based on the differences between the current data and the reference data in the form of absolute values, in order to consider the dynamic character of the system and the environment conditions, as demonstrated in

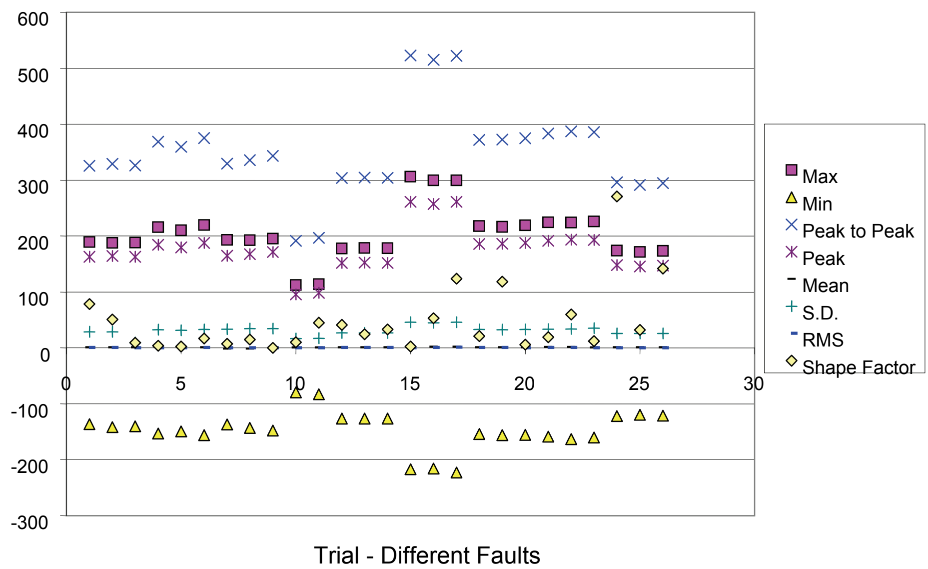

Figure 2: Statistical parameter example in the force signal for normal to reverse direction [McHutchon et al. (2005)].

reference [García Márquez et al. (2003)]. In Figure 3 are shown the as commissioned curves for current [A] vs. time [s] signals in the normal to reverse direction as result of the differences between the real data and the "as commissioned" data in the form of absolute values.

Pedregal et al. (2004) developed an algorithm based on the unobserved components (UC) class of models. The UC model fits into the discrete time multivariate models. This method can detect faults in real time, but for our study it has only been used for the purpose of filtering the signals. Figure 4 shows a smooth trend and an irregular signal. The trends are calculated as an estimate of the local mean of the series which is extrapolated into the future, and the irregular signals are a couple of unpredictable perturbations about such trends.

For a basic novel FDD, a typical 'As Commissioned' vector could be established using the mean of multiple trials of each individual point as part of set up. Then, calculating the correlation of each faulty vector with the 'Mean as Commissioned' vector will give a range of correlation values. If this range of correlations is sufficiently far from 1.0, then it will be possible to use this method for basic fault detection.

Mathematically, the correlation between two identically sized data sets is found in

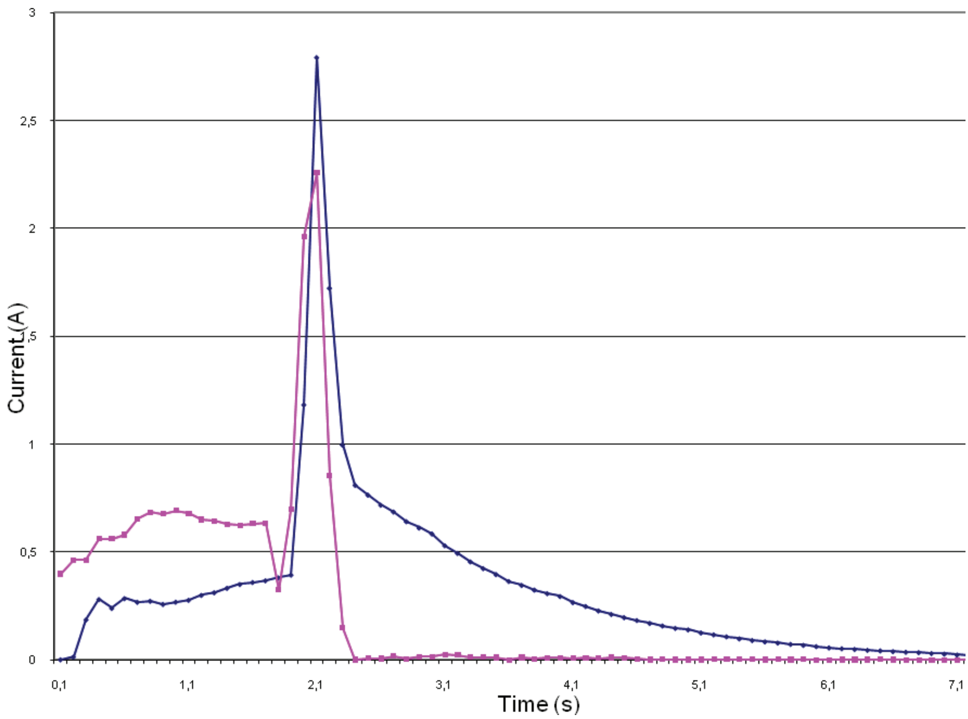

Figure 3: "As commissioned" curves for current [A] vs. time [s] signals in normal to reverse direction.

the explained manner, where *Cov* is the covariance, and σ and μ are the standard deviation and mean of the respective data sets x and y.

$$\rho_{xy} = \frac{cov(x,y)}{\sigma_x \sigma_y}$$

where $-1 \leq \rho_{xy} \leq 1$ and $Cov\,(x,y) = \frac{1}{n}\sum_{i=1}^{n}(x_i - \mu_x)\,(y_i - \mu_y)$.

This first stage of fault detection is only good for detecting whether a point may be in need of immediate attention. An ideal case would be where a fully functioning set of points gave force and current vectors that matched perfectly with test cases – returning a correlation coefficient of 1.0. Any faulty case would bring about sufficient change in the shape of the vector to noticeably affect the coefficient. Thus a novelty detecting algorithm could operate based on a threshold value of the correlation coefficient.

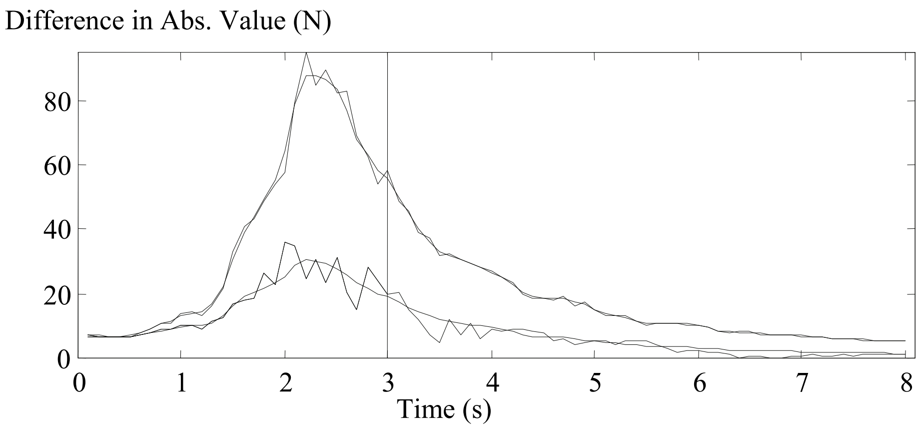

Figure 4: “As commissioned” curves filtered by UC models in normal to reverse direction [Zattoni (2006)].

In Table 1 the correlation factors for the current and force signals for normal to reverse (N-R) and reverse to normal (R-N) directions are presented. The signals studied are the signals from the experiment (exp.) and the signals that have been modified (mod.). It is clearly visible that the new signals considered in this paper differ more from the “as commissioned” signals than the original signals, so the faults can be classified better. For example, in N-R direction it was clearly identified 20% of the faults by analyzing the statistical parameters of the modified current signals, but it was not enough for detecting the rest of faults. It was improved studying the statistical parameters by pairs (see Figure 5). In this case every faults could be detected studying the modified current and force signals, and 70 % of faults in N-R direction and 65 % in R-N direction where identified.

The method still has a drawback which needs to be solved for a better implementation. The proposed method incorporated numerous statistical variables and turn increases the pairs of their combinations, hence making it very complex to control these combinations. So as to tackle this problem, principal component analysis (PCA) has been employed which reduces these numerous combinations to a smaller number of uncorrelated variables called principal components. The working steps of PCA have been explained herewith in detail.

Let **X** be a dataset, $\mathbf{X} \in \Re^{nxm}$ where $m$is the set of sensor values for each observation, arranged in each of n rows. PCA transforms this dataset X into a dataset in a transformed space given by the eigenvectors of the covariance matrix **S** associated

Table 1: Correlation factors for the experiments considering the experiment signals and the modified signals.

	Correlation Factor							
	Current				**Force**			
Fault	**N-R Direction**		**R-N Direction**		**N-R Direction**		**R-N Direction**	
	Mod.	**Exp.**	**Mod.**	**Exp.**	**Mod.**	**Exp.**	**Mod.**	**Exp.**
Tight lock reverse side (Sand on both bearers)	0.75917 0.57478 0.82615	0.74049 0.73558 0.92955	0.81295 0.84107 0.40678	0.92113 0.98102 0.98002	0.29745 0.30752 0.58850	0.98312 0.98445 0.99796	0.66339 0.65550 0.24093	0.98416 0.99963 0.98847
12mm obstruction reverse side at toe	0.80636 0.82126 0.81172	0.82120 0.88880 0.87179	0.46580 0.61699 0.62633	0.90279 0.89553 0.85432	0.67276 0.60521 0.58929	0.94763 0.99088 0.99187	0.69452 0.76518 0.76298	0.99968 0.99233 0.99158
Backdrive slackened, toe end LHS	0.70768 0.49343	0.79430 0.99227	0.58401 0.50831	0.99140 0.96786	0.38974 0.83553	0.98007 0.99803	0.06665 0.51106	0.99836 0.99979
Backdrive slackened, toe end RHS	0.92618 0.67939 0.75278	0.96604 0.97056 0.96278	0.71763 0.44013 0.54189	0.91518 0.93354 0.94422	0.32070 0.62378 0.35903	0.99815 0.99873 0.99660	0.16417 0.23716 0.57023	0.99333 0.99758 0.99582
Backdrive tightened, heel end RHS	0.58175 0.59979 0.85571	0.78459 0.98775 0.99454	0.66188 0.53864 0.09929	0.98992 0.99148 0.95114	0.35013 0.89630 0.94422	0.97768 0.99987 0.99850	0.84873 0.58756 0.37971	0.99991 0.99941 0.98958
Backdrive tightened, heel end LHS	0.93006 0.78312 0.58063	0.92901 0.98125 0.88833	0.14888 0.72314 0.80109	0.98397 0.99309 0.99279	0.59159 0.79395 0.32279	0.99508 0.99924 0.98526	0.44315 0.29150 0.74703	0.99389 0.99811 0.99988
Diode snubbing block disconnected	0.10428 0.69267 0.02669	0.77319 0.86849 0.74352	0.05410 0.76575 0.94722	0.89617 0.96403 0.82359	0.14728 0.49263 0.14642	0.99188 0.99993 0.98164	0.75536 0.52559 0.83611	0.99555 0.97966 0.99964
Drive rod stretcher bar loose RHS	0.74706 0.73818 0.72145	0.90492 0.89232 0.90019	0.51544 0.48233 0.46614	0.81079 0.81044 0.76758	0.54151 0.59636 0.58430	0.99442 0.99682 0.99373	0.85764 0.82996 0.85728	0.95092 0.95920 0.96605
Maximum	0.93006	0.99454	0.94722	0.99309	0.94422	0.99993	0.85764	0.99991
Minimum	0.02669	0.73558	0.05410	0.76758	0.14642	0.94763	0.06665	0.95092
Mean	0.67479	0.88354	0.55503	0.92443	0.52161	0.99050	0.57789	0.99011

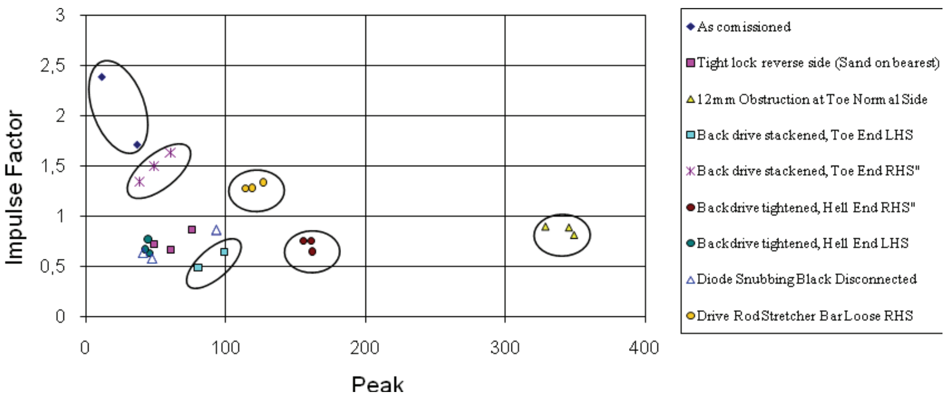

Figure 5: Impulse factor vs. peak factor of the force signal in Reverse to Normal direction.

with **X** (see equation 1).

$$\mathbf{S} = \frac{\mathbf{X}^T\mathbf{X}}{n-1} = \mathbf{U}\Lambda\mathbf{U}^T, \tag{1}$$

Where Λ is diagonal matrix of non-negative real eigenvalues with decreasing magnitude, $\lambda_1 > \lambda_2 > \ldots \lambda_{m-1} > \lambda_m$ ($\lambda_k \in \Re\ \forall k$), and **U** is matrix with columns being the corresponding eigenvectors.

Hence it has been deduced that the first principal component is accountable for as much of the variability in the data as possible, and each subsequent component accounts for as much of the remaining variability as possible [Jolliffe (1986)]. Each new eigenvector follows an ordered fashion so as to capture the maximum amount of variability in the dataset hereby giving rise to the principal components. A new p-dimensional set of Cartesian coordinates transformed from a new observation vector **X** has been obtained. Therefore **Y** is a projection of the dataset onto the principal component vector, where **P** ($\Re^{mxa}$) matrix gives the direction, a being the first largest eigenvalue with its columns being the retained eigenvectors.

For the purpose of this research, if there are j dimensions to the data then j eigenvectors should be found. The eigenvectors are associated with the statistical parameters presented above. Here d = 11, but for alarming and the prediction of faults, it is simplified to 2 and 3 dimensions.

It has been explored and verified that the faults can be grouped by linear relationship employing PCA and allowing detection of majority of faults, but only a few can be classified clearly. Figure 5 shows an example for force signal eigenvectors in the reverse to normal direction. A comparative study has been carried out with the results obtained by McHutchon et al. (2005) to establish better fault detection by analysis of the transformed signals, and in every case it has been possible to detect and classify faults.

4 Conclusions

A simple pattern recognition method has been employed in this pattern for detecting and identifying faults studying the different statistical parameters. In order to consider the dynamic character of the system, the experiment signal of current and force has been modified and filtered, employing unobserved component models. The new signals provide better detection and identification of the faults but it has been necessary to use a great number of graphics. In order to reduce this number, Principal Component Analysis has been applied. Using PCA, the faults can be grouped by linear relationship and every faults can be detected, most of them can be identified in both directions. The author proposes to study force and current graphics together for increasing the fault diagnosis reliability. In essence, the model performance is remarkably good when the signal is filtered, implying that the system described above is better for FDD of the devices involved. In addition, the system is capable of producing sensible forecasts of the future state of the system that allow the detection of potential failures before they occur in practice.

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References

Fry K. (1999): The Importance of Condition Monitoring in Providing Fault-Free Infrastructure. *Fault-Free Infrastructure Conference*, Derby, U.K.. pp. 17-25. Professional Engineering Publishing Limited.

García Márquez F.P., Pedregal D.J., Roberts C. (2010): Time Series Methods Applied to Failure Prediction and Detection. *Reliability Engineering & System Safety*, vol. 95(6), pp. 698-703.

García Márquez F.P., Roberts C., Tobias A. (2010): Railway Point Mechanisms: Condition Monitoring and Fault Detection. Proceedings of the Institution of Mechanical Engineers, Part F, *Journal of Rail and Rapid Transit. Professional Engineering Publishing*, vol. 224(1), pp. 35-44.

García Márquez F.P., Schmid F., Collado J.C. (2003): Wear assessment employing remote condition monitoring: a case study. *Wear*, vol. 255(7-12), pp. 1209-1220.

García Márquez, F.P., Schmid, F. (2007): A digital filter-based approach to the remote condition monitoring of railway turnouts. *Reliability Engineering and System Safety*, vol. 92, pp. 830–840.,

García Márquez, F.P., Lewis, R.W., Tobias, A.M., Roberts, C. (2008): Life Cycle Costs for Railway Condition Monitoring. *Transportation Research part E*, vol. 44, pp. 1175-1187.

García Márquez, F.P., Schmid F., Collado J.C. (2003): A reliability centered approach to remote condition monitoring. A railway points case study. *Reliability Engineering & System Safety*, vol. 80(1), pp. 33-40.

Jolliffe I.T. (1986): *Principal Component Analysis*. New York Inc: Springer-Verlag.

McHutchon M.A., Staszewski W.J., Schmid F. (2005): Signal Processing for Remote Condition Monitoring of Railway Points, *International Journal of Strain Measurement*, vol. 41(2), pp. 71-85.

Pedregal D.J., García Márquez, F.P.; Schmid, F. (2004): RCM^2 predictive maintenance of railway systems based on unobserved components models. *Reliability Engineering & System Safety*, vol. 83(1), pp. 103-110.

Roberts C., Dassanayake H.P.B., Lehrasab N., Goodman C.J. (2002): Distributed quantitative and qualitative fault diagnosis: railway junction case study, *Control Engineering Practice*, 10, pp. 419-429.

Shimonae T., Kawakami T., Miki H., Matsuda O., Tekeuchi H. (1991): Development of a monitoring system for electric point machines. *IRSE Aspect Int Conf*, 395-401.

Venkatasubramanian, V., Vaidyanathan, R., Yamamoto, Y. (1990): Process fault detection and diagnosis using neural networks I: steady state processes. *Computers and Chemical Engineering* 14(7), 699-712.

Zattoni, E. (2006): Detection of incipient failures by using an H_2-norm criterion: Application to railway switching points. *Control Engineering Practice*, vol. 14(8), pp. 885-895.

Zhou F.B., Archer N., Bowles J., Duta M., Henry M., Tombs M., Zamora M., Baker S., Burton C. (2002): Remote condition monitoring and validation of railway points, *Computing & Control Engineering Journal*, vol. 13(5), pp 221-230.