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Time-Domain Stator Current Condition Monitoring: Analyzing Point Failures Detection by Kolmogorov-Smirnov (K-S) Test

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Abstract**—**This paper deals with condition monitoring of electric switch machine for railway points. Point machine, as a complex electro-mechanical device, switch the track between two alternative routes. There has been an increasing interest in railway safety and the optimal management of railway equipments maintenance, e.g. point machine, in order to enhance railway service quality and reduce system failure. This paper explores the development of Kolmogorov-Smirnov (K-S) test to detect some point failures (external to the machine, slide chairs, fixing, stretchers, etc), while the point machine (inside the machine) is in its proper condition. Time-domain stator Current signatures of normal (healthy) and faulty points are taken by 3 Hall Effect sensors and are analyzed by *K-S* test. The test is simulated by creating three types of such failures, namely putting a hard stone and a soft stone between stock rail and switch blades as obstacles and also slide chairs' friction. The test has been applied for those three faults which the results show that *K-S* test can effectively be developed for the aim of other point failures detection, which their current signatures deviate parametrically from the healthy current signature. K-S test as an analysis technique, assuming that any defect has a specific probability distribution. Empirical cumulative distribution functions (*ECDF*) are used to differentiate these probability distributions. This test works based on the null hypothesis that *ECDF* of target distribution is statistically similar to *ECDF* of reference distribution. Therefore by comparing a given current signature (as target signal) from unknown switch state to a number of template signatures (as reference signal) from known switch states, it is possible to identify which is the most likely state of the point machine under analysis.

Keywords**—**stator currents monitoring; railway points; point failures; fault detection and diagnosis; Kolmogorov-Smirnov test; time-domain analysis;

I. Introduction

THE regular observation and measurement of characteristics of a system is called condition monitoring, which is a powerful tool to enhance reliability, availability, safety and efficiency of any system [1].

Considering the lack of efficiency in traditional maintenance strategies, such as operate to failure or fixed time maintenance, developing fault detection and diagnosis (*FDD*) tools and algorithms are focused in recent years. The initial aim of such *FDD* algorithms is earlier detection and diagnosis of the faults before they cause critical failures of the system, improving the availability and maintainability of the systems [2].

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One of the main problems in any fault detection and diagnosis (*FDD*) scheme is detecting the change(s) in the parameters of the given stochastic process, as a change in the mean of the process while the variance is constant or as a change in the variance of the process while the mean is constant. Such parametric changes may be a symptom of fault occurrence in a realization of a random process, measured as time series and may be abrupt or gradual and temporary or permanent [3]. Also change occurrence point(s), the effect of the change occurrence on the level of the series, their particular type, size and duration are from parameters which should be considered for assessing the faulty state.

Identifying change(s) may be an initial step for the *FDD* process and designing any fault detection system. For this aim, an algorithm should be developed to detect any changes, comparing to the normal healthy series. This would be possible by a comparison between healthy and faulty series, to detect any probable parametric changes.

Some parametric and nonparametric tests have been developed for testing the similarity between two distributions [4]. In parametric test, the parameters such as mean and variance of the two distributions are compared, whereas in nonparametric tests the empirical cumulative distribution function (*ECDF*) of the two distributions should be compared. Kolmogorov-Smirnov test, as a nonparametric test, is designed for the *FDD* purpose, assuming that any defect has a specific probability distribution. The K-S test, as time-domain signal processing technique is designed for the aim of comparing the *ECDF* of a given signatures from unknown condition (as target signal) with a number of template signatures from known conditions (as reference signal), to conclude that the two sets of data originate from the similar state.

The faults of the switches can be defined in two categories. Category I includes the faults related to the switch blades and external switch components (outside the machine) and category II includes the mechanical and electrical failures of the point machine components, such as bearings, gears, ball screw and lead screw faults or a combination of them.

As the input for the proposed fault analysis scheme, the time-domain stator current signatures of the switches are sampled from the motor for normal and faulty states. According to the current signals, in all assessed faults of the category I, the faulty current signature deviates in parameters such as the mean and variance, from its normal condition, while in all faults of the category II, faulty stator current signature is similar to its normal condition (without any parametric changes). Since there would not be any difference between faulty and healthy state for the category II of switch's faults, the category I is only chosen for change assessment.

The category I includes the following failures:

- Slide chairs friction
- Existing an obstacle between stock and switch rails to prevent switch locking
- Damage to the blades and etc…

Considering the obtained samples, faults of the category I can cause a deviation in level or mean of the stator current series, from reference mean value μ_0 toward μ_1. In time series analysis approach, such change points are usually known as intervention [5]. In this paper fault occurrence in the underlying process, is only assessed. This means that the series with intervention(s) would be differentiated from normal series. For this aim, the *K-S* test is then developed based on processing the *ECDF* of the stator current series of some faults of the category I. In section II, the stator current signals of the motor are sampled in the normal and faulty states from the switches. Then the Kolmogorov-Smirnov test is explained in section III which should be then applied on obtained samples. The experimental results are shown in section IV.

II. Experimental Analysis

Fig. 1 represents the current signal of the motor in the normal (healthy) state of the system. The signal is sampled with the rate of 5 KHz for 8 seconds. The operation time of the machine is about 5.5 seconds.

Since level change is shown on DC signals, the envelope of the signal is extracted and analyzed in this work. Fig. 2 represents the envelope of the AC current signal, after implementing a low pass filter, in order to clear the signal from the noises with high frequencies.

In this investigation, among all failures related to the faults of category I, three faults were studied. They were namely inserting a soft and a hard stone (obstacles) between the stock and the switch rails and slide chairs friction. Due to existence of an obstacle in this location, the locking mechanisms of the point machine and switch system will not perform correctly.

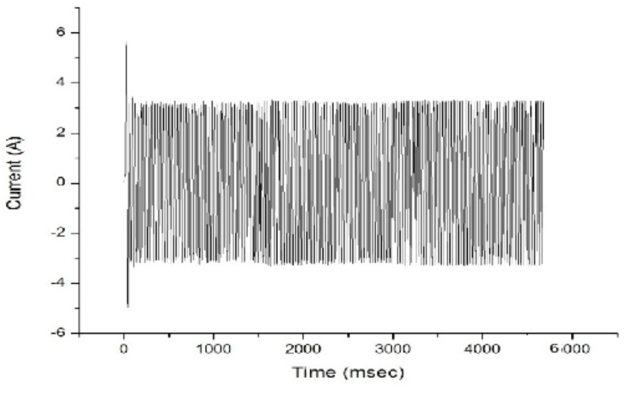

Fig. 1 AC current signal in the normal state of the point machine

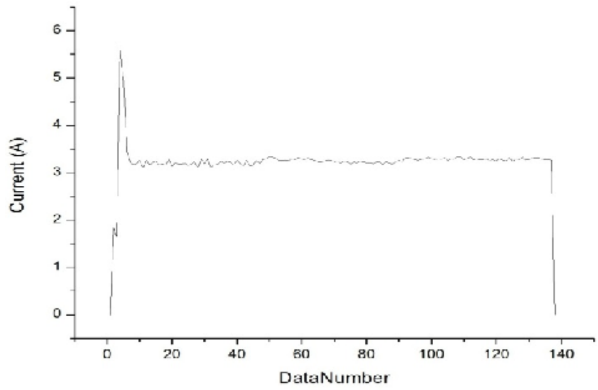

Fig. 2 the AC current envelope signal in the normal state of the point machine

Fig. 3, 4 and 5 show the stator current signal for the three simulated faults. As the figures show, for the case of slide chairs' friction, the level of the stator current signal increases gradually and permanently, as a result of increases in the friction force and extra forces needed to perform system locking. On the other hand in the case of existence of a hard obstacle in the gap, one intervention is expected to occur in the stator current signal. The single intervention point may be due to the backward force applied to the motor, after the switch blade contacts the obstacle. The increase in the level of the current signal continues, until the motor supply is disconnected by the control circuits.

In the case of soft stone, two interventions in the current signal are detectable. The first intervention is due to interruption in the switch blade movement, when it hits the stone. The soft stones are normally broken to pieces, under the load applied by the motor. This enables the blades to move further, until the stone pieces will stop the blades again, in a position related to their sizes. Hence the first intervention may be followed by a short period stationarity in the level of the signal, before the second intervention happens. The blades might be able to finish their movement course and be locked, if the stone is broken to very small pieces. In this case the switch is ready to be used by the train with minimum risk, although a maintenance action is recommended before any train moves over it. The current series would be stable for the rest of the operation performance cycle. In each figure the intervention points are shown by arrows.

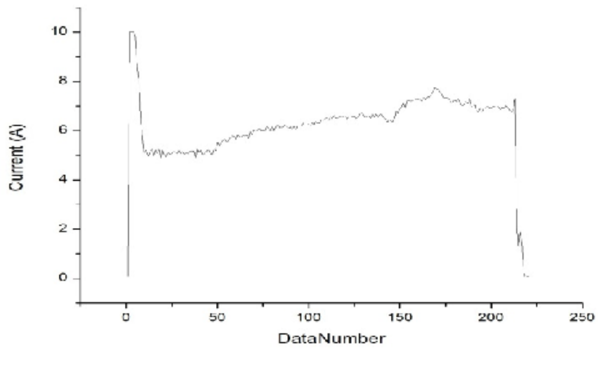

Fig. 3 Motor current signal in faulty state of the point machine: Slide chairs friction

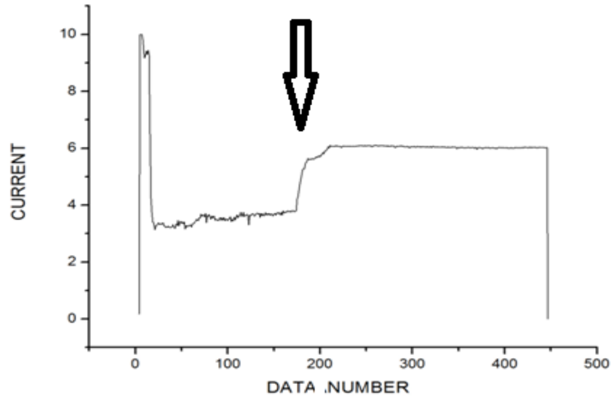

Fig. 4 Motor current signal in faulty state of the point machine: hard stone in the gap

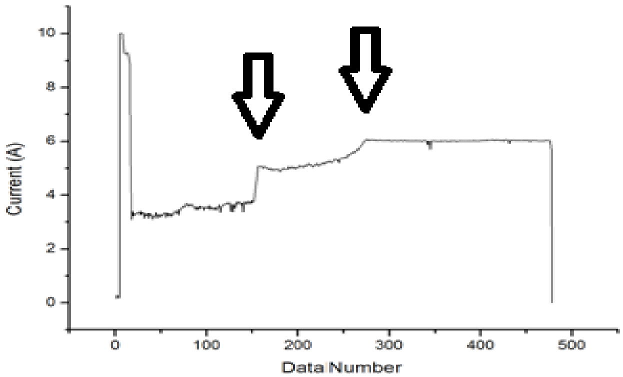

Fig. 5 Motor current signal in faulty state of the point machine: soft stone in the gap

III. KOLMOGOROV-SMIRNOV TEST

The K-S based signal processing technique is a simple time-domain methodology which compares two signals, namely $F_1(X)$ or reference signal of known state and $F_2(X)$ or target signal of unknown state. The algorithm tests the hypothesis that the two signals have the same *ECDF*. Using the technique it is possible to determine whether the two signals are similar or not. So by comparing a given current signature (target) to a number of template signatures (reference), i.e. signatures from known switch conditions it is possible to determine which the most likely condition of switch under analysis is.

The application of this test for condition monitoring assumes that the fault is strong enough to vary the *ECDF* of original current signature, which is the case of point failures. ECDF of reference and target signals are denoted by $F_1(X)$ and $F_2(X)$ respectively.

For the aim of fault detection, normal signals are chosen as $F_1(X)$ set and all normal samples and faulty samples of hard and soft obstacles are chosen as $F_2(X)$ set. Each time a specific sample from each set is selected and the K-S test is then applied in order to determine the similarity in each pair. Briefly such comparison is done in order to test the algorithm's ability to detect faulty and healthy samples in the $F_2(X)$ set. The stages are as follows:

1. Determine a specific signal of known state as $F_1(X)$, where the random variables X are arranged in ascending order.
2. Calculate D statistic for each pair of $F_1(X)$ and $F_2(X)$ signals, as maximum absolute difference between $F_1(X)$ and $F_2(X)$ given by (1) (X_i is the random variable at *i*th position);

$$D = \max \left| F_1(X_i) - F_2(X_i) \right| \quad -\infty < i < \infty \tag{1}$$

3. Calculate Q_{K-S} or K-S probability distribution function by (2), where λ is a function of two parameters, namely D and Ne, (N_1 and N_2 are the number of data points in $F_1(X)$ and $F_2(X)$ sets respectively and Ne is the effective number of data points);

$$p-value = Q_{K-S}(\lambda) = 2\sum_{i=1}^{\infty}(-1)^{i-1}e^{-2i^2\lambda^2}$$

$$\lambda = (\sqrt{Ne} + 0.12 + \frac{0.11}{\sqrt{Ne}})D \quad ; \quad Ne = \frac{N_1 N_2}{N_1 + N_2} = \tag{2}$$

$$Q_{K-S}(\lambda) = \begin{Bmatrix} 1 & \lambda \to 0 \\ 0 & \lambda \to \infty \end{Bmatrix}$$

4. Test the null hypothesis that the two distributions are equal at significant level $\alpha = 0.05$, by the following Hypothesis testing:

$$H = \begin{Bmatrix} 0 & P-Value & > \alpha \\ 1 & P-Value & < \alpha \end{Bmatrix} \tag{3}$$

An increase in the magnitude of *P-Value, (i.e. above* 0.05), indicates that the *ECDFs* of two reference and target signals are similar. In this case the magnitude of *D* will be trivial. On the other hand, the small value of *P-Value* indicates the difference between the two signals. If *P-Value* is equal to zero, then the two signals are completely different [6]-[9].

IV. EXPERIMENTAL RESULTS

In this investigation, 16 stator current signals of the motor are sampled separately for each of the normal and the three faulty states namely hard stone in the gap, soft stone in the gap and slide chairs friction. For the aim of point failure detection, the 16 normal samples are chosen as reference signal and all the 54 normal and faulty samples are chosen as target signal. So healthy or faulty state of any given signal of unknown state would be detected by a comparison with reference signals of healthy state.

Here we assume that the normal signals of the reference set are of known state, and the faulty and normal signals of the target set are unknown which their type should be then determined. The distance value *D* and the corresponding P-Value are considered as fault indicators and should be calculated in each pair of the $F_1(X)$ and $F_2(X)$ signals. In fact, for each pair of signals, which its related *P-Value* is greater than 0.05, the target signal is similar to the reference signal and should be then determined as normal signal. Hence by applying the *K-S* test, the normal and faulty signal would be identified in the target set and the faulty state would be diagnosed.

Fig. 6 and 7, show the *ECDFs* of a particular current signature at normal state (red line) as reference signal, that is compared with two faulty current signatures of different type, namely existence of hard and soft stone in the gap (blue line) as target signal respectively. As mentioned in section II, one and two intervention points are predictable for the faults of hard stone and soft stone in the gap respectively, and hence deviation from stationary level may happen once in the level of the series for the former and twice for the latter respectively. The intervention occurrence is obvious from each figure which has affected the *ECDF* of the normal stator current series and has been detected by the K-S test.

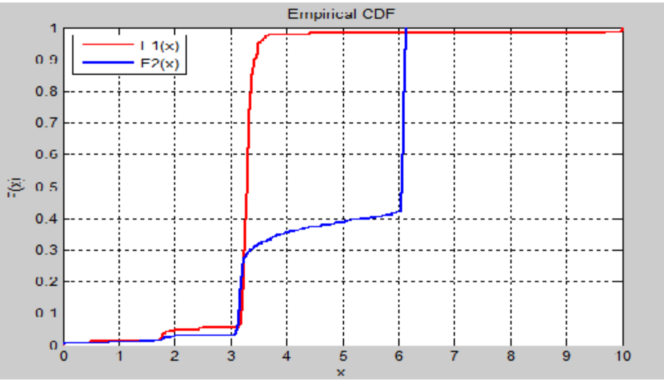

Fig. 6 ECDFs of a particular normal current signature (red line) and a faulty signature of existing Hard stone in the gap (blue line)

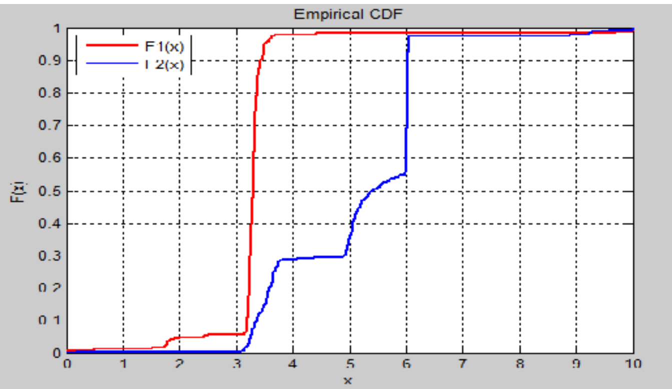

Fig. 7 ECDFs of a particular normal current signature (red line) and a faulty signature of existing Soft stone in the gap (blue line)

Fig. 8 shows the *ECDF* of current signatures at normal state as reference signal (red line) that is compared with a current signature at faulty state of slide chairs friction as target signal (blue line). As mentioned in section II, deviation from stationary level may happen gradually in the level of the series. The change occurrence is obvious from the figure which has affected the *ECDF* of the faulty stator current series.

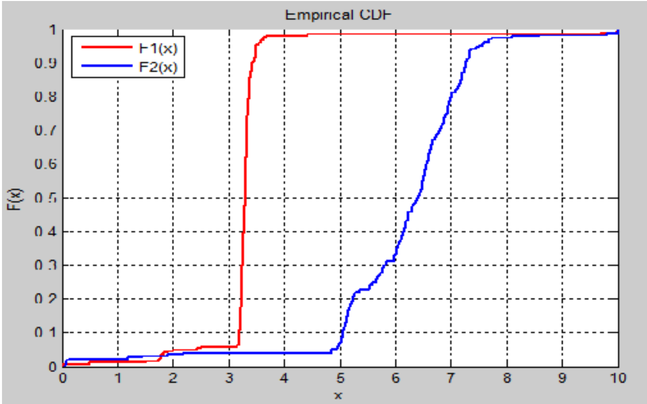

Fig. 8 ECDFs of a particular normal current signature (red line) and a faulty signature of Slide chairs friction (blue line)

The *ECDFs* of 5 various stator current signatures, for each of the three simulated faulty states, are shown in Fig. 9 (A), (B) and (C) separately. For each fault type all faulty series as target signal are compared among themselves and with a particular normal current signature as reference signal. As can be seen, although the target signals are different in some characteristics, but deviation from normal state is significantly obvious for all samples of the simulated faults, and hence the K-S test is able to detect the faulty state successfully when a normal signal is chosen as reference signal.

According to figure 9, differences in characteristics of the signals, under similar conditions, are noticeable. This can be due to load variation conditions, in-consistence in the operation conditions of the system and also the size and magnitude of the obstacles. The characteristics of the stator current signature, namely the intervention point(s), change size, duration, type, starting and stopping phases of the switch's cycle, maximum power and etc would be influenced by some parameters such as motor's speed, the obstacle's characteristics and external conditions, hence be variable for different samples of particular type. Consequently the *ECDF* and the corresponding *P-Value* of the current signal would be affected by load variation. Such influences may reduce chance of the K-S test's ability to detect the similarity among faulty series of particular type and failed then to diagnose the exact state of the underlying faulty signal correctly. This means that by choosing a reference signal of particular fault type, we cannot surely say that any given target signal of unknown state, which the corresponding *P-Value* is smaller than 0.05 is not similar to the state of the reference signal. So to confirm the obtained results by the K-S test it is recommended to implement another input such as vibration signatures for the aim of condition monitoring or apply other methods.

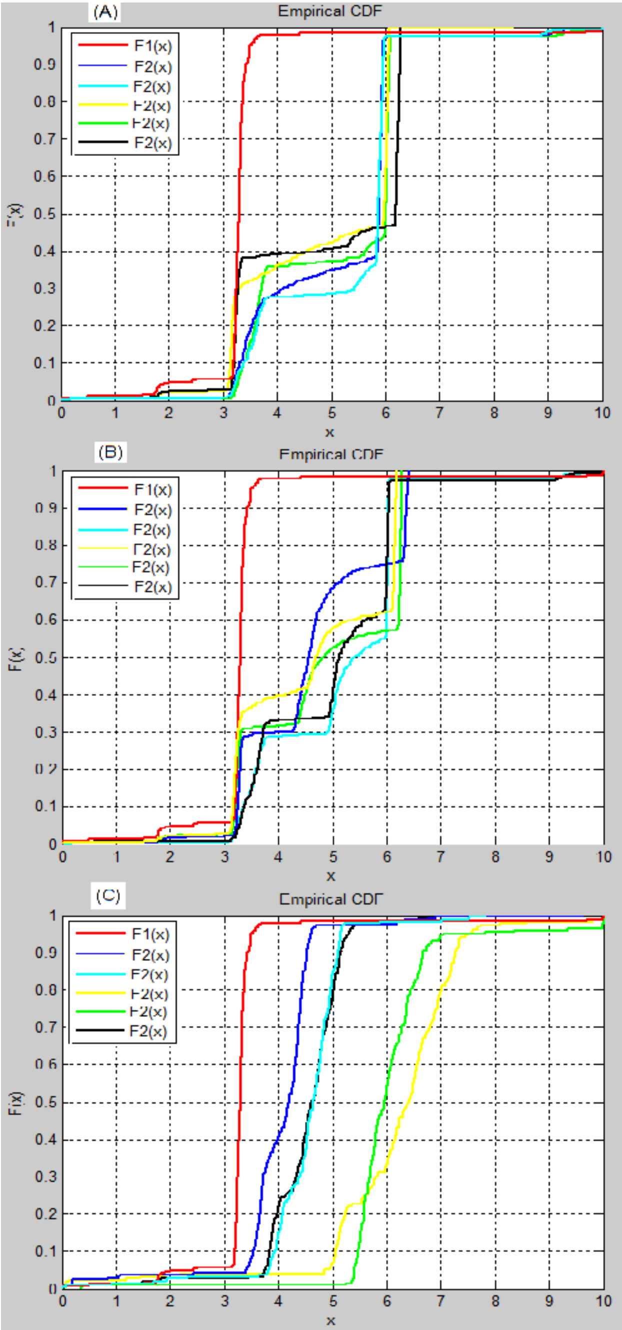

Fig. 9 ECDFs of a particular normal current signature (red line) and 5 various faulty signature of: (A): Hard stone in the gap (B): Soft stone in the gap (C): Slide chairs friction

The outcome of the *K-S* test which applied on 20 normal and faulty series is shown in table I. According to the *P-Values*, the algorithm has detected normal and faulty series correctly. The *P-Values* (*P*) greater than 0.05 indicate similarity between reference and target signals (*H=0*), on the other hand values less than 0.05 indicate faulty state (*H=1*).

V. Conclusion

In this paper the Kolmogorov-Smirnov test is used in order to identify change occurrence in the level of the stator current of the motor for three simulated faulty states, namely existence of soft and hard obstacles (stone) in the gap between stock and switch rails and also slide chairs friction. By using the K-S test, a comparison can be made between a healthy current signal as reference signal and a given signal of unknown state, to determine the healthy or faulty state of the unknown series. Hence by using the test, faulty signals would be identified based on the obtained *P-Value* between two samples. Although this test applied on 3 types of point's failures, but can be developed for more fault types, in which the current series deviate parametrically from normal state. In fact for the category of switches failures, that the mean or variance of the series changes abruptly or gradually, this method may be efficient.

A considerable result shows that this method is not sufficient for fault diagnosis purpose. This means that by choosing a reference signal of particular fault type, we cannot surely say that any given target signal of unknown state, which the corresponding *P-Value* is smaller than 0.05 is not similar to the state of the reference signal. Because some other parameters, such as current signature characteristics and etc influence on the *ECDF* of the signal and may cause in wrong results. Analyzing the stator current signatures of a wider range of faults would help us to develop more efficient fault detection and diagnosis system for the point failures.

TABLE I
K-S Test Parameters for Stator Current Signatures of the Motor,, for Normal Signals and 3 Simulated Faults, Namely Hard Stone in the Gap (H), Soft Stone in the Gap(S) and Slide Chairs Friction (F)

		N1	N2	N3	N4	N5
N1	**P**		0.386	0.714	0.873	0.0530
	H		0	0	0	0
N2	**P**		0	0.099586	0.242053	0.0496
	H		0	0	0	0
N3	**P**			0	0.365666	0.07514
	H			0	0	0
N4	**P**				0	0.0636
	H				0	0
N5	**P**					0
	H					0
H1	**P**	3.72e-27	4.03e-46	3.66e-34	1.20e-22	2.12e-27
	H	1	1	1	1	1
H2	**P**	1.59e-20	2.75e-44	7.31e-40	2.44e-22	1.00e-20
	H	1	1	1	1	1
H3	**P**	2.49e-21	8.33e-91	8.39e-46	2.44e-61	1.45e-21
	H	1	1	1	1	1
H4	**P**	6.82e-21	1.41e-87	6.84e-46	6.41e-59	3.79e-21
	H	1	1	1	1	1
H5	**P**	5.40e-22	4.24e-45	2.14e-40	1.96e-22	3.29e-22
	H	1	1	1	1	1
S1	**P**	4.28e-20	6.44e-45	2.86e-39	2.22e-22	2.71e-20
	H	1	1	1	1	1

S2	**P**	2.49e-21	6.67e-87	8.39e-46	2.20e-60	3.33e-21
	H	1	1	1	1	1
S3	**P**	1.27e-18	1.49e-47	1.70e-43	5.30e-24	2.55e-19
	H	1	1	1	1	1
S4	**P**	4.94e-15	2.21e-32	1.78e-17	1.26e-24	1.42e-63
	H	1	1	1	1	1
S5	**P**	4.32e-17	1.06e-61	1.39e-16	3.18e-17	1.86e-26
	H	1	1	1	1	1
F1	**P**	8.46E-62	7.97E-88	2.62E-83	3.79E-60	1.34E-49
	H	1	1	1	1	1
F2	**P**	3.74E-61	3.63E-85	2.74E-79	4.98E-59	2.44E-49
	H	1	1	1	1	1
F3	**P**	5.30e-24	2.55e-19	2.35E-92	1.42E-63	1.14E-10
	H	1	1	1	1	1
F4	**P**	5.74E-89	8.43E-98	3.38E-67	3.53E-92	6.17E-53
	H	1	1	1	1	1
F5	**P**	1.00E-85	1.08E-93	8.90E-68	6.33E-53	9.89E-24
	H	1	1	1	1	1

REFERENCES

[1] B. O. Oyebande and A. C. Renfrew, "Condition monitoring of railway electric point machine", *IEEE Proc.-Electr. Power Appl.*, Vol. 149, No. 6, 2002.

[2] A. Kelly and M. J. Harris, "Management of industrial maintenance", Butterwords, London, 1978.

[3] M. Bassevile and I. V. Nikiforov, "Detection of abrupt changes, Theory and Application*", Prentice-Hall International, INC*., 2005.

[4] C. Kar, A and R. Mohanty, "Application of KS test in ball bearing fault diagnosis", Journal of sound and vibration, Vol. 269, 2004.

[5] Cannon Jordan, "Statistical analysis and algorithms for online change detection in real time physiological data*", Master thesis*, 2009.

[6] X. Wang and V. Maxis."Autoregressive model-based gear shaft fault diagnosis using the Kolmogorov-Smirnov test", Journal of Sound and Vibration, Vol. 327, 2009.

[7] Feiyun Cong, "Kolmogorov-Smirnov test for rolling bearing performance degradation assessment and prognosis", Journal of vibration and control, Vol. 17, No. 9, 2010.

[8] C. Kar and A. R. Mohanty, " Multistage gearbox condition monitoring using motor current signature analysis and Kolmogorov-Smirnov test", Journal of Sound and Vibration 290, pp. 337-368, 2006.

[9] LD. Hall and D. Mba, "Acoustic emmissions diagnosis of rotor-stator rubs using the KS statistic", Mechanical Systems and Signal Processing, Vol. 18, 2004.