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Fault detection in railway point drive supported by data mining methods

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In this work diagnostics of railway point drive supported by Data Mining methods was considered. Results of FEM calculations of switching forces acting on the considered point are qualitatively correct, so Data Mining methods efficiency was examined on data obtained from FEM multi-body model. Hidden structures in data and patterns describing particular faults were identified. Proposed algorithms of Kohonen's neural networks and k-means clustering are easy to apply to classifying. Their implementation on the Digital Signal Processor is not difficult and memory consumption is low so diagnostic module supported by implemented Data Mining methods was proposed in order to preliminary asses technical state of railway points and to assure current state monitoring and supporting maintenance activities.

Keywords: artificial neural networks, data mining, diagnostics

1. Introduction

Increase in the maximum speed of trains on railways with simultaneous modernization of railway traffic control equipment requires development of their diagnostic systems. For the purposes of safety of railway traffic, diagnostics of point drives performance is particularly important.

Methods that are currently used base on preventable diagnostic strategy, which is time-consuming and economically none-effective. Switching forces measurements are performed every two months with respect to railway regulations [12]. Thus faults are usually detected when their influence on railway point is significant and requires immediate maintenance. Development of the computer infrastructure makes it possible to apply monitoring systems to railway points, continuously send data to operators' station and save it in database.

On the British Railways monitoring systems record measurements of DC current and DC voltage, motor speed and movement waveforms during a switching operation. Transient analysis of current waveforms based on the summed squared error comparison between measurements and the laboratory tests results was carried out. Similar analysis was held for speed, throwing time and movement and also for the Power Spectrum Density of current. As a robust solution the net energy analysis technique was proposed. It involves calculation of the net energy for voltage and current measurements with application of identified values of motor resistance and moment of inertia [7]. On the Japanese high-speed rail network, a condition monitoring system has been developed using load and current sensors [8].

On the German Rail (DB) network the status of the points is diagnosed on the basis of the proportionality between the throwing force and the active power input of the motor. The timing of the control current and voltage during the point throwing operation is recorded in this process. An active-power curve is generated from the established power and voltage values as a function of time. The computer adjusts the measured active power by the influence of the ohmic losses through the cable cores and the stator resistance of the point machine motor. Therefore the ohmic loop resistance has to be measured during commissioning and saved in the master data in the system for each point. The calculated active-power curve is compared for evaluation, with limiting values stored in the system. The limiting values are calculated automatically for each individual point on the basis of the properties of point type, point lock type, and point machine type stored in the system [9].

In works [6] the measurements of railway point switching current and voltage were pointed as adequate source of information concerning technical state of railway point identification.

Railway point type EES-5 is one of the most widespread types on railways in Poland.

Increasing resistance of switching is the straight way to the point fault. It may result from different faults i.e. resistance in one or both blades motion, slide blocking, resistance of head or bar, change of blades stiffness, break of blockade, geometry changes in bar-clamp system and others. Identification of relations describing influence of individual faults on movement resistance rises possibility of point diagnosing on the basis of switching current and voltage measurements. Monitoring system of railway point performance saves in database measurements of mentioned quantities for each switching of the point. It results in huge amount of data. In such a case patterns characteristic for changes in switching forces due to particular faults are hidden in data. Since the identification of hidden patterns in data is one of the goals of Data Mining methods [11], an attempt to construct the diagnostic module supported by these methods was made.

Measurements of voltage in power system and current while railway point is being switched provide important parameters connected to technical state of point and drive. Switching forces are identified by calculating electrical power and transforming it into values of moments and loads using parameters of drive provided by manufacturer. So monitoring system database includes both measured electrical quantities and calculated forces. Monitoring system mentioned above is in testing stage now, so it is a good time to propose and test algorithms of automatic data analyses for diagnostic module. Simplicity of algorithms was assumed due to requirements of their implementation on the Digital Signal Processor, which will assure preliminary assessment of railway point state for sending it to database and operators' station.

Examples of measurements for different faults have not been collected yet so data obtained with the use of the Finite Elements Method were considered to test proposed algorithms.

2. FEM MODEL

Multi body model was build. It includes two modules: drive consisting of electric engine, gear, mechanism of slide, switching pole and railway point that includes blades of point, resistant rails, clamp locks, runner of clumps.

For the model of railway point system, on the basis of data provided by the manufacturer, detailed analyses of loads having effect on elements of mechanism were carried out.

All the considered mechanisms were modelled as rigid body elements since their deformations have slight influence on switching forces values. Only the blades were modelled as finite elements due to their significant influences on switching forces values. In rigid body elements resistance loads are more important than resilience. In order to obtain high quality of calculated switching forces values, the kinematics system with dynamic characteristics was created.

At the first stage, the values of loads were obtained on the basis of system geometry. Loads characteristics were calculated with the use of the multi-body model simulation method.

Inertia of cross sections was used to determine the load required to bend a blade with desired value. One of the primary resistance loads is friction load generated on blade bags. It varies in the wide range in comparison with the other friction loads. Its value was obtained as resistance friction generated by complete masses of blades in the geometric middle of blade. In Fig. 1 there is presented the considered model.

Characteristic of switching forces changes during switching obtained with the use of the FE Method for properly working point is presented in Fig. 2.

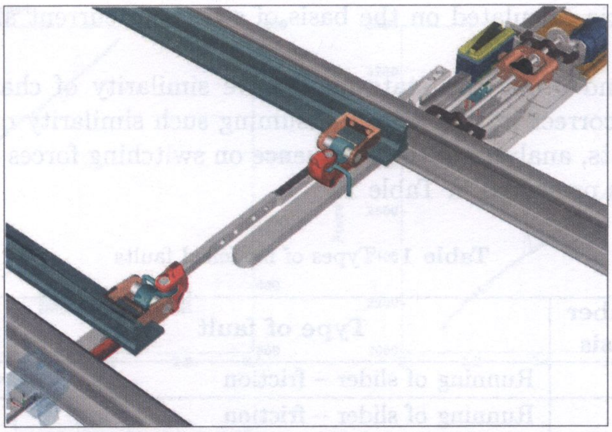

Fig. 1. Multi body model

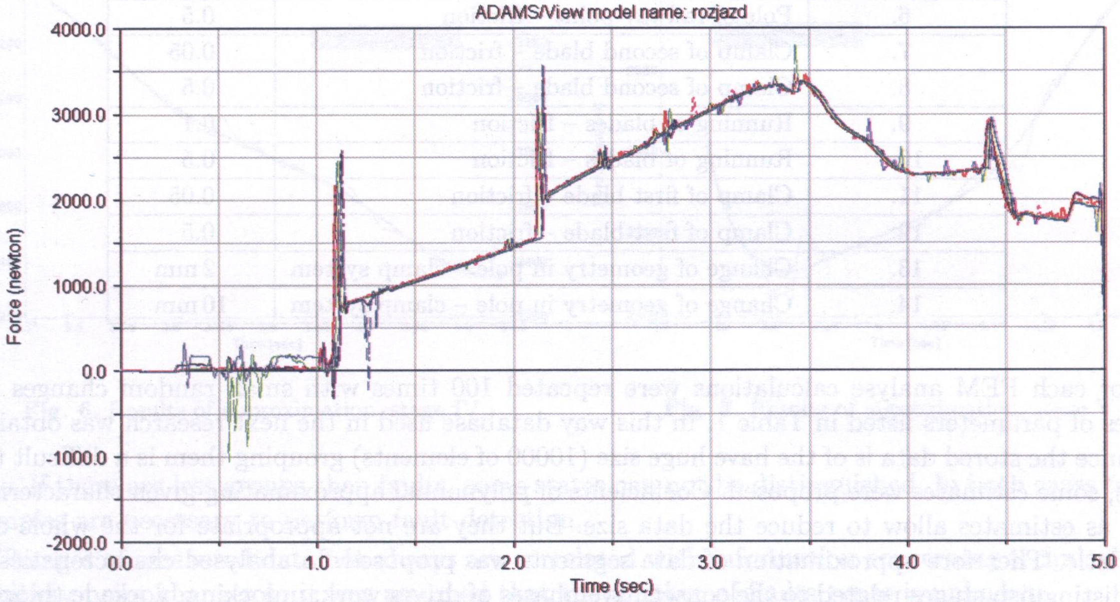

Fig. 2. Characteristic of switching forces – FEM Model

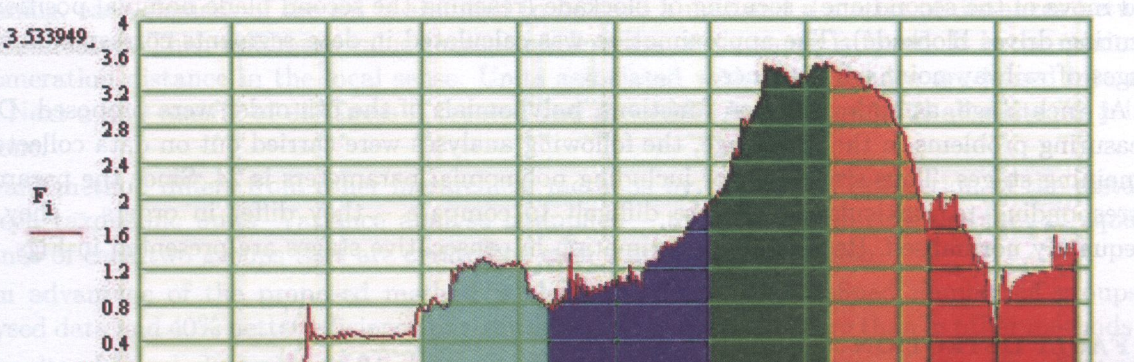

Fig. 3. Characteristic of switching forces – measurements

Adequate characteristic calculated on the basis of switching current and voltage measurements is presented in Fig. 3.

Comparing Figs. 2 and 3 one can state qualitative similarity of characteristics and that the consider FEM model is correct in that sense. Assuming such similarity of characteristics obtained for different types of faults, analyses of their influence on switching forces changes were carried out. List of modelled faults is presented in Table 1.

Table 1. Types of modelled faults

C – Number of analysis	Type of fault	Value of parameter
1.	Running of slider – friction	0.05
2.	Running of slider – friction	0.5
3.	Running of head – friction	0.05
4.	Running of head – friction	0.5
5.	Pole of railway point – friction	0.05
6.	Pole of railway point – friction	0.5
7.	Clamp of second blade – friction	0.05
8.	Clamp of second blade – friction	0.5
9.	Running of blades – friction	0.1
10.	Running of blades – friction	0.5
11.	Clamp of first blade – friction	0.05
12.	Clamp of first blade – friction	0.5
13.	Change of geometry in pole – clamp system	2 mm
14.	Change of geometry in pole – clamp system	10 mm

For each FEM analyse calculations were repeated 100 times with small random changes near values of parameters listed in Table 1. In this way database used in the next research was obtained.

Since the stored data is of the have huge size (10000 of elements) grouping them is a difficult task. Thus, some estimates were proposed. Coefficients of polynomial approximating given characteristics used as estimates allow to reduce the data size. But they are not appropriate for the whole characteristic. Therefore approximation of data segments was proposed. In analysed characteristics one can distinguish stages related to the consecutive phases of drives work: unlocking blockade (blockade opening with the use of slide mechanism), switching of the first blade (first blade movement and coupling of second blade clamp into working position), both blades switching (blades movement and reaching end of working range of first blade), first blade locking (locking clamp of the first blade and move of the second one), securing of blockade (reaching the second blade nominal position and securing drives blockade). The approximation was calculated in data segments corresponding with stages of railway point performance.

At each stage, as approximation functions, polynomials of the 5th order were proposed. Due to measuring problems in the first stage, the following analyses were carried out on data collected for remaining stages. Thus size of vector including polynomial parameters is 24. Since the parameters corresponding to particular stages are difficult to compare – they differ in orders – they were adequately normalised. Results of approximation in consecutive stages are presented in Figs. 4–7.

3. Fault detection

The first aim of the work was to determine number of groups appearing in data. Number of groups can suggest how many patterns are hidden in data but it does not have to equal the number of faults. Characteristics of switching forces qualified into the same group can identify different failures. If there are more groups than faults, some of them identify the same states or characterise unrecognised

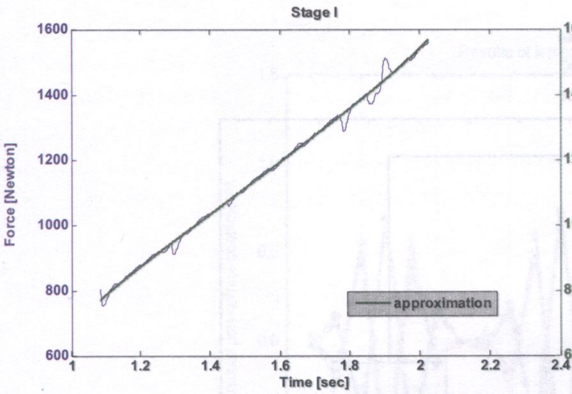

Fig. 4. Results of approximation, stage II

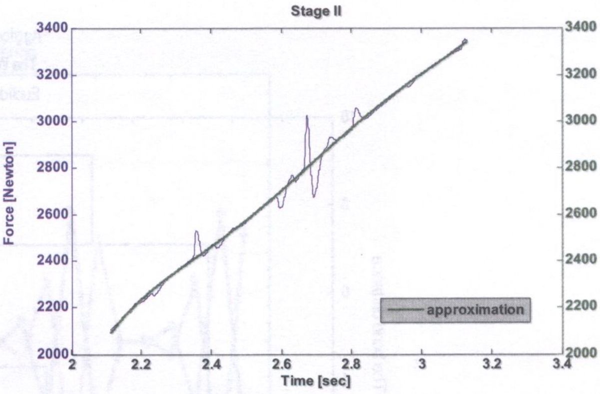

Fig. 5. Results of approximation, stage III

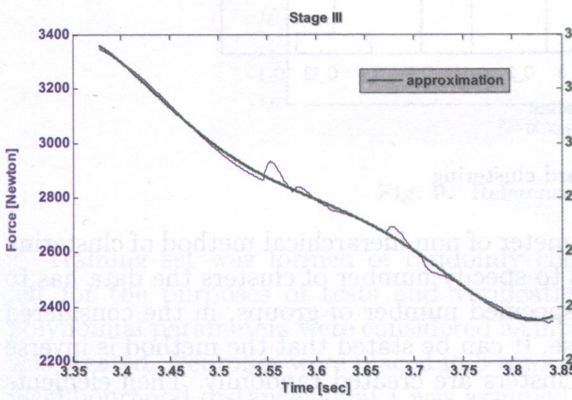

Fig. 6. Results of approximation, stage IV

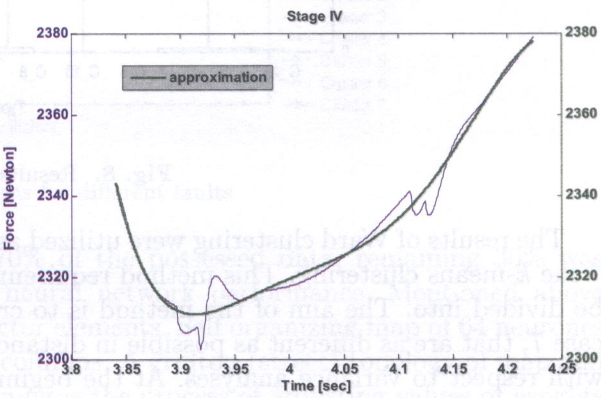

Fig. 7. Results of approximation, stage V

state. If there are less groups then faults, some states can not be distinguished. In both cases testing examples are necessary to perform fault detection.

Changes of measured data not always are correlated with information concerning technical state of railway point changes so it was assumed that the number of faults types is unknown.

For such defined clustering task Ward method was chosen. It is one of the hierarchical agglomeration methods. Methods of this type allow to specify hierarchical tree of elements of analysed set. The tree is being built via step by step joining of operational taxonomic units into subsets. At the beginning, each element of the set is assumed to be such a unit and a matrix of distances between units is created. Then minimum value (except of elements of diagonal) is found. It is the minimum agglomeration distance in the local sense. Units associated with this distance are joined into new unit. Next a new matrix of distances is created and procedure is repeated until all units are joined into one.

Ward method differs from other hierarchical methods by the way of estimation of the distance between taxonomic units. Variance analyse is applied – towards minimizing the sum of squared distance of each two groups that are created at each step of agglomeration.

An advantage of the proposed method is the lack of arbitrary defined number of groups in analysed data and 40% better efficiency of right detection of data structure than in other methods [1].

Results of Ward clustering of 24 elements vectors including parameters of approximating polynomials are shown in Fig. 8.

The Ward tree can be cut on the level where bond distance equals 1. By doing so the number of groups in data was identified as 7. It is possible to read from the tree which types of examples belong into particular group.

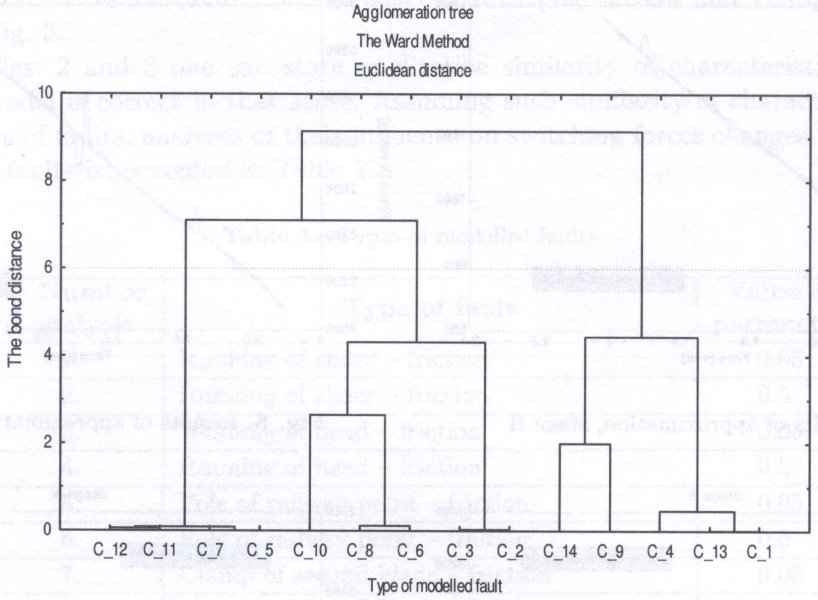

Fig. 8. Results of Ward clustering

The results of Ward clustering were utilized as parameter of non hierarchical method of clustering – the k-means clustering. This method requirement is to specify number of clusters the data has to be divided into. The aim of the method is to create specified number of groups, in the considered case 7, that are as different as possible in distance sense. It can be stated that the method is inverse with respect to variance analyses. At the beginning clusters are created randomly. Then elements of the set are being moved from one cluster to another to assure minimum variety in cluster and maximum variety between clusters.

In the considered case study the aim of the k-means method application was to determine which types of faults are grouped together and what are reference values characteristic for each cluster.

Results of the k-means clustering are presented in Fig. 9 and in Table 2.

In comparison, both methods: k-means clustering and Ward method provide the same sets of cluster contents.

Table 2. Results of k-means clustering

Cluster no	Type of modelled case
1	C14
2	C9
3	C2 C3
4	C1 C4 C13
5	C5 C7 C11 C12
6	C10
7	C6 C8

Results obtained above proved that some simulated faults are qualified into the same group – they can not be distinguished. Therefore efficiency of artificial neural networks was investigated. The advantage of neural networks application is good noise robustness, which is very important in case of real operational measurements conducted on railway points. Other advantages are ability to detect early changes in data [2] and user friendly graphical presentation of present technical condition. Assuming the lack of information concerning analysed data structure the Kohonen's neural networks in self organizing feature maps version were proposed.

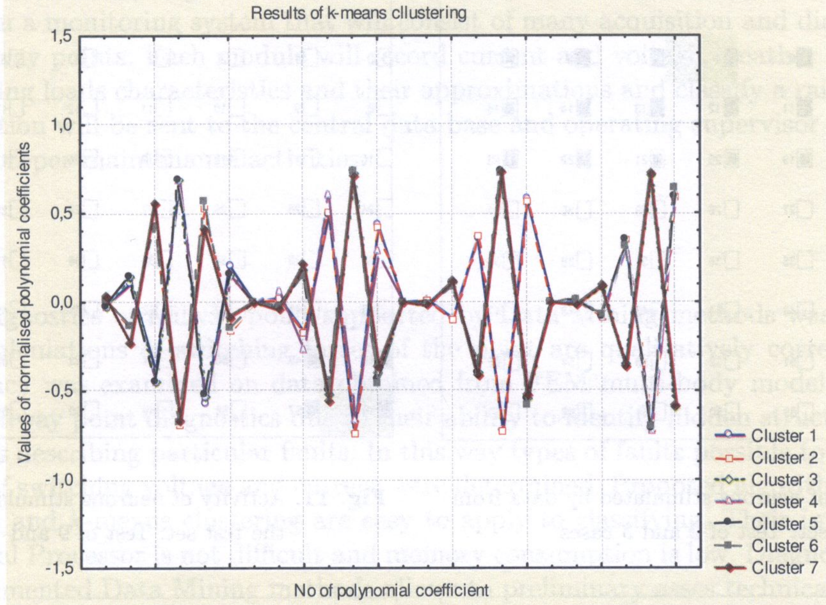

Fig. 9. Reference patterns for different faults

Training set was formed of randomly chosen 70% of the possessed data, remaining 30% was left for the purposes of tests and verification of neural network performance. Mentioned above polynomial parameters were considered as input vector elements. Self organizing map of 64 neurones was created. Neurones were placed in 8 rows and 8 columns. A gridtop (street) topology of map and neighbourhood distance equal 1 was assumed. Training is the process of adjusting values of weights according to Eq. (1) [10].

$$\begin{aligned} w_{ni}(t) &= w_{ni}(t-1) + \eta \cdot (x(t-1) - w_{ni}(t-1)), \\ w_{nj}(t) &= w_{nj}(t-1) + 0.5\eta \cdot (x(t-1) - w_{nj}(t-1)), \qquad \text{for } j \in \varepsilon_i\,, \end{aligned} \tag{1}$$

where w_{ni} – weight of the ith wining neuron nth connection, ε_i – neighborhood of ith neuron, $x(t-1)$ – input data vector, η – learning rate.

After the training process the neural map was tested. Obtained results are presented in the Figs. 10–13. For testing examples one can identify regions of map – sets of neurons that are active when input to the map is corresponding to data representing particular types of faults. Neurones checked in Fig. 10 are active for data characteristic for faults of type 2 and 3. Faults of type 14 and 9 stimulate neurones 48, 49, 56, 57 (Fig. 11). Large group of neurones responds to data of 5, 7, 11, 12 types. (Fig. 12). Another region of the map is active when data of 6 and 8 types are analysed (Fig. 13). There are also some single neurones detecting data of the same type. Neurone no 58 detects examples of data of types 1, 4 and 13. Data of type 10 stimulate neurone no 26.

It is worth noticing that obtained self organizing map identified six groups in data. The difference according to the Ward method is that faults of type 14 and 9 are in the same group. But analyzing Ward tree one can easily find that for bond distance of 2 there are six groups. Two groups consisting of examples of faults of type 14 and 9 are joined at this level of bond distance.

Obtained results proved that some faults are difficult to detect with utilisation of measurements of switching forces. Another reason of this problem is selection of estimators, some of which poorly discriminate data. Also modelled failures may have slight influence on railway point switching forces.

But considering six groups identified in data, corresponding to the technical state of railway point, it is worth to build a state classifier. The result of the k-means clustering is a set of patterns identifying group centres. It is easy to classify the railway point state just comparing coefficients of polynomial approximating calculated switching forces characteristic with identified patterns. For neural network application the coefficients are compared with the weight vector of each neuron.

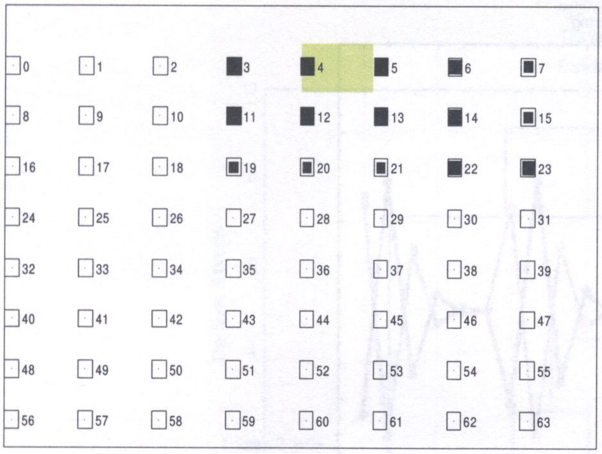

Fig. 10. Activity of neurons stimulated by data from the test set: Test of 2 and 3 cases

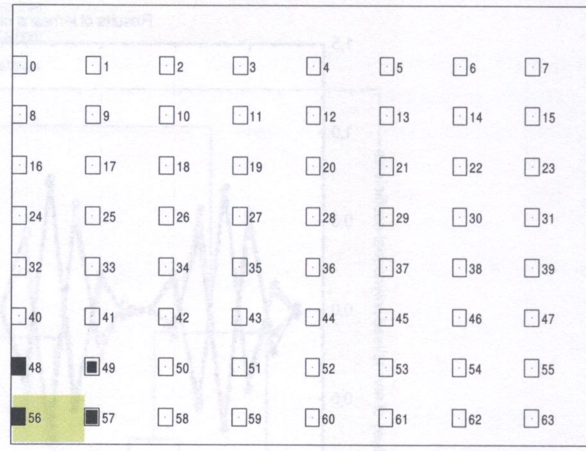

Fig. 11. Activity of neurons stimulated by data from the test set: Test of 9 and 14 cases

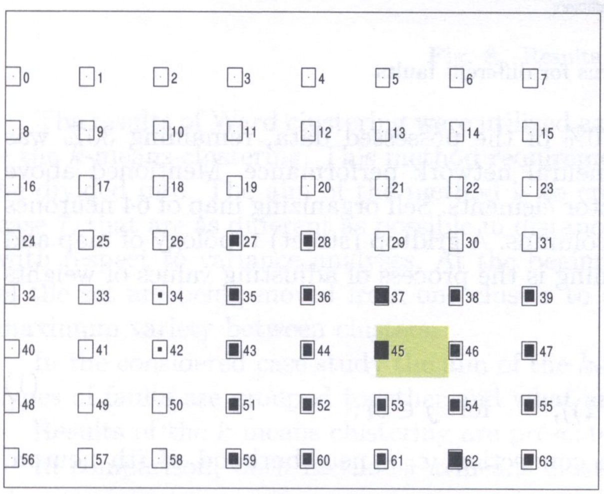

Fig. 12. Activity of neurons stimulated by data from the test set: Test of 5, 7, 11 and 12 cases

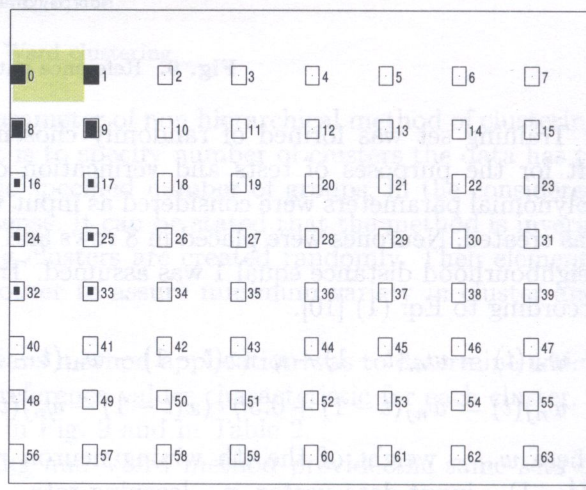

Fig. 13. Activity of neurons stimulated by data from the test set: Test of 6 and 8 cases

Only the neuron with weights closest to the coefficients values fires due to Kohonen's competitive rule. Since each neuron has its ordinal number the sets of numbers of neurons firing in particular machinery state were collected using information obtained above. Now it is easy to classify the railway point state checking active neurone's affiliation to desired sets of neurones. There are also neurones outside specified sets but they don't fire because their weights are too much different from the values of the coefficients. In case they are active they can be used to signal unrecognized state.

Both methods of classification that were mentioned above, are easy to implement on the Digital Signal Processor.

So the future research will be performed in two stages: implementation of Data Mining algorithms supporting classification of the railway point technical state and tests of algorithms on true data measured via acquisition module mounted on a real railway point.

Since the real data differs slightly from simulated it is necessary to adjust patterns used in the k-means algorithm and adjust weights of the Kohonen's neural network. These values will be used in Digital Signal Processor to classify condition of the railway point. At this moment prototype acquisition module is recording data from one point. Short exploitation period results in only one railway point state. It makes impossible to adjust patterns and weights. But in a few months collected measurements will allow to adjust values necessary for proper diagnostic module performance. It will be applied in a monitoring system that will consist of many acquisition and diagnostic modules mounted in railway points. Each module will record current and voltage, weather information, will calculate switching loads characteristics and their approximations and classify a railway point state. All this information will be sent to the central data base and operating supervisor in order to make decision about proper maintenance activities.

4. Summary

In this work diagnostics of railway point supported by Data Mining methods was considered. Results of FEM calculations of switching forces of the point are qualitatively correct. Data Mining methods efficiency was examined on data obtained from FEM multi-body model. These methods are helpful in railway point diagnostics due to their ability to identify hidden structures in data and identify patterns describing particular faults. In this way types of faults possible to detect basing on measurements of switching voltage and current were determined. Proposed algorithms of Kohonen's neural networks and k-means clustering are easy to apply to classifying. Their implementation on the Digital Signal Processor is not difficult and memory consumption is low. Diagnostic module supported by implemented Data Mining methods allows to preliminary asses technical state of railway points and assures current state monitoring and supports maintenance activities.

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