Diagnosis of the electrical motors of a train using self-organised maps

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***Abstract*--This paper describes the use of neural networks based on self-organising maps in order to diagnose the health conditions of induction motors in trains operating daily services around Madrid, Spain. This kind of neural networks is used for the creation of models able to characterise the normal behaviour of the electrical motors of the train. These models will allow for the on-line detection as soon as possible of any anomaly that could evolve into a failure. The models formulated use non-intrusive measurements taken from different points of the train. They are based on the measurement of electrical currents and axial and radial vibrations on the electrical motor. This is part of an expert system existing at a higher level named the Intelligent System for Predictive Maintenance Applied to Trains (ISMAPT) which monitors and diagnoses some components of the above mentioned trains.**

***Index Terms*—Electrical train, electrical motor, diagnosis on-line, predictive maintenance, neural network, self-organising map, expert system.**

I. INTRODUCTION

Today, the maintenance of massive transport vehicles is a key point due to the important social function that they perform and the great number of vehicles in each fleet. A high level of reliability, availability, quality of service and security is required in order to perform their function. This paper is an application in the railway world where all of these factors are important reasons to apply suitable maintenance plans.

The application of predictive maintenance is one of the most effective ways to prevent, or at least mitigate, degradation of some components, loss of their functionality and sudden presence of failures. The detection of such problems and the diagnosis of their root causes are very important for all railway companies. Early diagnosis of a problem can stop, or at least mitigate its impact in the operation, as well as increase the reliability and availability of public trains at a minimum cost[9].

The term diagnosis comes from the Greek word "dia gignoskein", i.e. "knowing the difference" [10]. This means that diagnosis involves the act of distinguishing one case from another. In order to do this it is necessary to characterise the condition of an element belonging to the process and also the knowledge needed for the evaluation of this condition is required [4]. Both tasks can be defined as the monitoring of the element and the diagnosis of itself and they are key concepts to apply effective predictive maintenance techniques.

Electrical motors are relevant components in any kind of industry due to the key function that they perform. The prevention of their faults has been the objective of different technologies and methods that can be found in the related literature [3, 5, 13]. Artificial Intelligence techniques, like Artificial Neural Networks (ANN), have recently proven in many applications that they can be useful instruments to know the health condition of electrical motors [1, 2, 11, 12] using information about different measurements of their performance.

This paper describes the main features of the methodology used for early detection of faults in the electrical traction motors of a train named UT450 manufactured by the company ALSTOM and belonging to the Spanish railway company RENFE. This methodology is based on a kind of ANN named Self-Organised maps in order to know if the current performance observed in the electrical motor corresponds or not, to its normal behaviour [6, 7, 8].

This methodology is integrated inside an intelligent software tool (ISPMAT) specially designed for the diagnosis and application of predictive maintenance to some components of an electrical train.

The organisation of the paper is as follows. First, the main features and objectives of the ISPMAT application are presented. Next, the main parameters of the electrical motors of the train UT450 are listed. Finally, the application of self-organised maps to the detection of shaft unbalance and degradation of bearings of the electrical motors of the train are presented as examples of the ISPMAT application.

II. ISPMAT APPLICATION FOR THE DIAGNOSIS OF THE UT450 TRAIN

The most effective way to know the real condition or health of equipment or of industrial processes is the continuous monitoring and diagnosis of them.

Generally speaking, the implementation of a complete and integrated monitoring and automatic diagnostic system (collection of data, detection of faults and reasoning about their root causes) is not too extensive. The most part of the modern industrial processes are analysed by very good continuous monitoring systems able to collect important variables for the operation of equipment or processes. They usually include the detection of critical levels of variables, and can also detect critical situations and avoid damage, not only to equipment, but also to people and the environment. Normally these monitoring systems are specific systems that, having been developed with standard tools and protocols for monitoring components and processes, usually work in an isolated manner inside a more complex system and do not perform an automatic diagnosis. In all of these monitoring systems the analysis of the information and the final decisions are performed by expert technical personnel. The automation of this analysis phase in order to complete the automatic diagnosis is being introduced in an increasing manner by using some intelligent diagnostic systems or expert systems.

The Institute for Research in Technology, IIT (which stands for the Spanish name, Instituto de Investigación Tecnológica) is an institute which belongs to the Pontificia Comillas University in Madrid, Spain. IIT has developed, in collaboration with ALSTOM Transport Division and RENFE, the Spanish railway company, both also located in Madrid, a project named the Intelligent System for Predictive Maintenance Applied to Trains (ISPMAT). The objective of ISPMAT is the automatic detection and diagnosis of faults, or symptoms of faults, in two components of the type of train referred to as UT 450, owned by RENFE, based on artificial intelligence techniques. This process allows for the application of maintenance precisely at the most suitable moment, saving money that would otherwise be spent on unnecessary dismounts and replacements, and inconveniences due to the unavailability of the train.

ISPMAT is a versatile system that can be applied to any component of the train. The components currently monitored by ISPMAT in the UT 450 train are the compressor and the elements in the traction bogies of the train. This kind of trains perform continuous services daily around Madrid in an approximate radius of 60 Km.

ISPMAT is a software application able to collect information from different types of sensors and to pass it through the different software modules. After this, the user can immediately obtain the diagnoses associated with the information collected and he can decide if a maintenance action should be executed or not. All of this can be performed at the moment when the train arrives to the depot, and also, on-board the train during its normal services.

The detection of faults and diagnoses does not require the dismounting of any component in the train, saving time and money in respect to the current practice of inspection of the train. However, it does require the installation of a set of sensors that can be re-used for testing different trains coming to the depot or can be installed permanently into the train if the diagnosis will be performed on-board. A multi-channel device is in charge of the collection of the information generated by the sensors and its convenient translation to be used by the other modules of the ISPMAT application. The architecture of ISPMAT is presented in Fig. 1.

In order to reach its objective, the ISPMAT application performs the following sequence consisting of three steps:

a. Data acquisition from sensors installed in the train.
b. Analysis of the data collected in order to discover anomalies.
c. If an anomaly is discovered, a diagnosis process, based on an expert system, is executed in order to find its root cause of the problem.

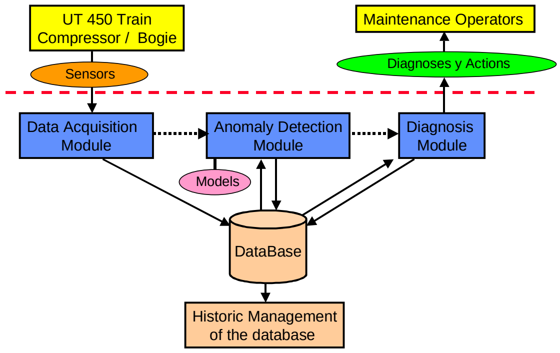

Figure 1. ISPMAT architecture

The main concern of this paper will be with step b dedicated to the analysis of the data collected in order to discover anomalies. This analysis is done by neural networks models based on self-organising maps and information from tests obtained inside the ISPMAT project related to the induction motors of the bogie of the UT 450 train. A description of these models will be described in the next sections.

III. ELECTRICAL MOTORS OF THE TRAIN UT450 AND FAILURE MODES TO BE DETECTED

The diagnostic system ISPMAT is intended for electrical trains of the Spanish Railway Company RENFE constructed by ALSTOM. Such trains are often referred to as commuter trains because they are used for fast and massive transport of passengers in urban and suburban services. The trains have two floors and accommodate up to 190 seated passengers per carriage. Each train can be made up of two different types of carriages: the conventional passenger carriages and the engine or passenger carriage with driver cabin included.

There are two engines in a UT 450 train. Each one has two bogies with two induction motors at the ends of the train (4 electrical motor per engine) and weighs 86.7 tons. The engine consists of the driver cabin, the control equipment compartment and a compartment for 128 seated passengers. The supply voltage is DC with a voltage of 3kV that is converted to AC. Each motor delivers a maximum power of 740kW, leading to a total maximum power of 1480kW for the whole engine.

The use of several vibration, speed and current sensors in the bogie makes it possible to measure the mechanical and electrical behaviour of the train bogie. The sensor signals are subject to the following procedures: signal conditioning, A/D conversion, pre-processing, and FFT.

The acquired data form the primary source of information for the modelling process.

Fig. 2 shows a scheme of a UT 450 bogie. This paper will concentrate on the analysis of the vibrations obtained from the sensors located at points 2V and 1V that are the ends of one electrical motor in the bogie. These vibrations are obtained at a radial direction of the electrical motor. The information at these points can be used for the detection of the following failure modes: degradation in the bearings at both ends of the motor, unbalance of the motor shaft and coupling problems. These failure modes have been selected taking into account that ISPMAT will be based on non-intrusive measurements. Obviously, other kind of failure modes could be detected in the electrical motor, but they would require dismounting of some parts of the train and it is not feasible due to cost of the operation. The main idea is that ISPMAT can perform a fast diagnosis of a train when it is coming to de depot in order to decide if it is necessary to dismount the bogie or not. Also, ISPMAT can be running on-board the train during its normal service. In this case, ISPMAT can inform remotely to the depot if some problem is detected in order to be ready for a correction of it. In both cases, ISPMAT helps to optimise the application of maintenance resources.

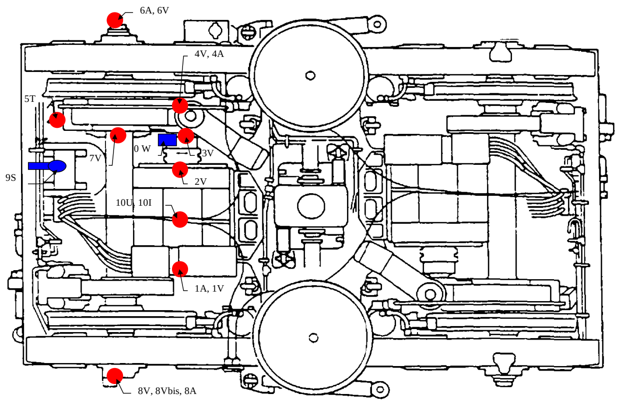

Figure 2. Scheme in plant of a UT 450 bogie

IV. SELF-ORGANISED MAPS MODELLING THE VIBRATIONS AT THE ENDS OF THE ELECTRICAL MOTOR

Two vibration sensors are located at the ends of the electrical motor in radial direction. One of them is near to the coupling side at the drive end. It is named “motor_r_lr” (point 2v in Fig. 2). It is expected that this point has smaller vibration levels than the other end named “motor_r_lor” (point 1V in Fig. 2). This is because the electrical motor is free at the non-drive end (point 1V in Fig. 2) and attached to the coupling at the drive end (point 2V in Fig. 2).

Several tests have been performed both when the train is running a normal service with passengers (coupling running with load) and at the train depot in a special facility where the train can be raised some millimetres from the railway (coupling running without load).

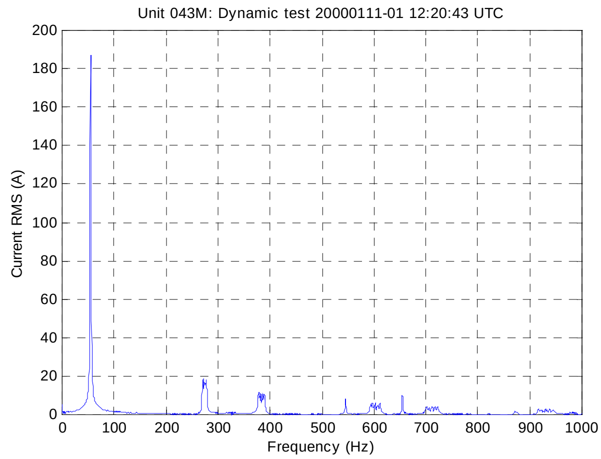

Figure 3. Spectrum of current when the train is running

Fig. 3 shows the typical current spectrum of one of the phases during a dynamic test performed on January 1st 2000. It can be seen a first harmonic at about 50 Hz, this frequency is related to the train speed (84.212 km/h) in this example. At higher frequencies several harmonics may appear depending on the condition of the train (accelerating or applying electrical breaks). The analysis of the currents allow to know the working condition which affects the vibration behaviour because it depends on the torque level and sign. During dynamic tests the levels of vibration at the motor are much higher that in the depot, because of vibration induced from the rails and vibrations generated at the gearbox and coupling when torque is present. The RMS global values of vibration at measurement point 1V in Fig. 2, during a sequence of tests performed on unit 043M is shown in Fig. 4. These vibration levels are much higher than those that will be presented in Fig. 5 observed at the depot.

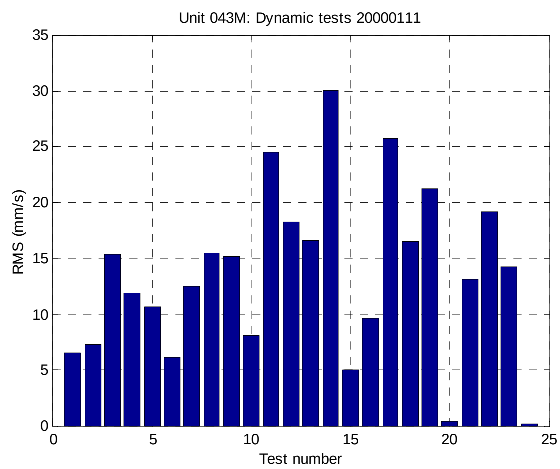

Figure 4. Vibrations at the point 1V when the train is running

As it has been shown, in normal service the effect of the movement of the train on the railway introduces noise and disturbances in the vibrations, for this reason neural network models have been created using the data taken at the train depot. There, cleaner spectres of signals have been obtained and used in the rest of the paper.

The tests used for the creation of models based on self-organising maps correspond to speeds at 30 and 70 km/h in both turn directions of the electrical motors of several trains of the series UT 450.

In order to obtain a robust model, an estimation of the energy at multiples of the characteristic frequency (frequency of the motor turn) is performed and also, a segmentation of the spectrum is made in wide windows, trying to characterise the vibrations.

Equation (1) defines the segmentation applied. This is estimated like the RMS value in a window from component l to component u.

$$V_{rms} = \sqrt{\sum_{i=l}^{u} V_i^2} \tag{1}$$

The different RMS values from the windows that are considered will be the inputs to the neural network models. The spectrum information below 100 Hz was not used due to excessive noise.

A. Vibrations at the non-drive end of the electrical motor "motor_r_lor" (coupling opposite side)

Fig. 5 shows a typical spectrum corresponding to the measurement collected at the point 1V in Fig. 2.

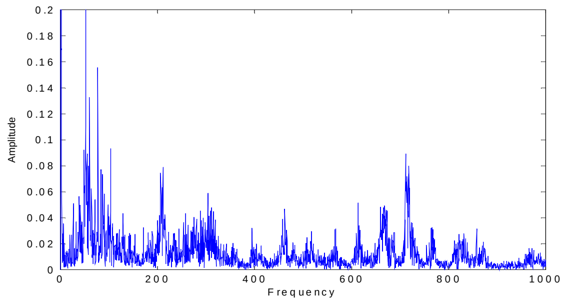

Figure 5. Vibrations at the point 1V when the train is tested at the depot

Significant dynamics of frequencies are observed between 400 and 850 Hz (this will be labelled as high frequencies), and also surroundings to 125-200 Hz (this will be labelled as low frequencies). Segmentation was made in these two windows.

Fig. 6 shows the results of the application of the segmentation algorithm to all the available tests in both windows.

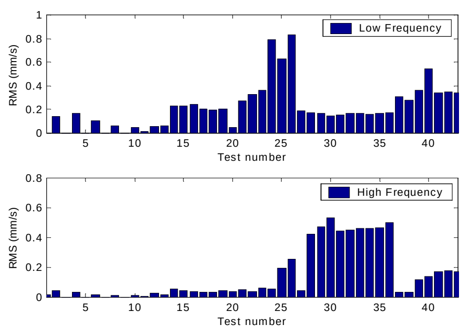

Figure 6

A Kohonen map (6x6 neurons) was trained with these two inputs. The error obtained is very low and its value is 0.02943. Fig. 7 shows the map and two partial maps corresponding to each input.

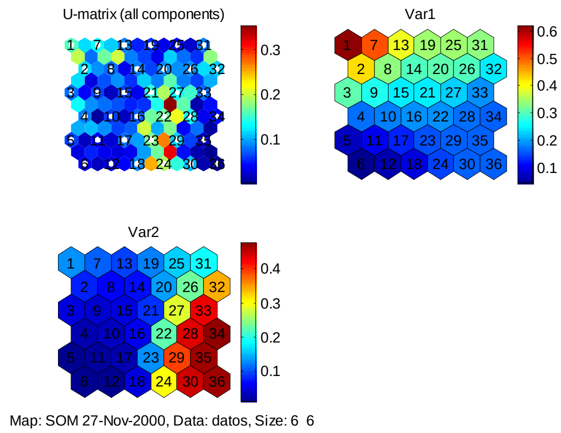

Figure 7

From Fig. 7 and further analysis, four clusters can be obtained:

- Cluster 1: High vibrations at low frequencies: (neurons 1 7)
- Cluster 2: High vibrations at high frequencies: (neurons 28 30 34 35 36)
- Cluster 3: Medium vibrations at low frequencies: (Nneurons 3 8 19 25)
- Cluster 4: Low vibrations: (rest of neurons)

Following, Table I shows the number of tests classified inside each cluster:

	C1	C2	C3	C4
Hits	4	9	7	23

Table I

The model detects those electrical motors which have a spectrum with high energy (4 cases in C1) and that have to be analysed in detail by the diagnostic module of ISPMAT in order to find the root cause for the high vibrations. The high vibration detected by the model does not mean that the electrical motor has a problem, but it could be possible. The model detects only that there is not a normal behaviour similar to that of other electrical motors.

B. Vibrations at the drive end of the electrical motor "motor_r_lr" (coupling side)

Fig. 8 shows the results of the application of the segmentation algorithm to all the available tests only in the window of low frequency. The high frequency window does not have significant information at this point of measurement.

A Kohonen map (6x6 neurons) was trained with this input. The error obtained is very low and its value is

0.02647. Fig. 9 shows the map and the partial map corresponding to the input.

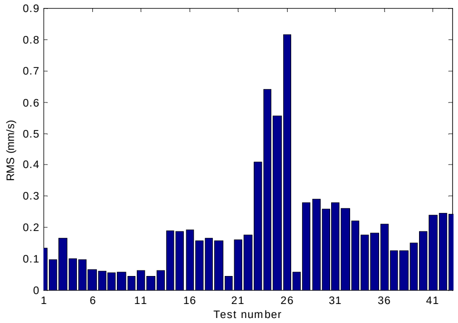

Figure 8

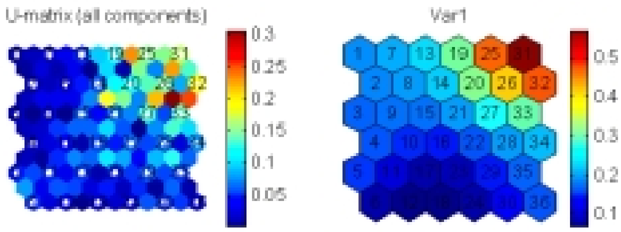

Figure 9

Using the same procedure of analysis as in the previous case, three clusters were obtained:

- Cluster 1: High vibrations: (Neurons 26 31)
- Cluster 2: Medium vibrations: (Neurons 27 33)
- Cluster 3: Low vibrations: (Rest of neurons)

Following, Table II shows the number of tests classified inside each cluster:

	C1	C2	C3
Hits	4	5	34

Table II

Similar conclusions to the previous analysis in the point motor_r_lor were obtained. Four tests are classified in the cluster of high vibration, 3 of them are the same tests that had also been classify as high vibrations by the previous model. These tests correspond to same unit, which has been classified as anomalous in all 4 tests performed.

C. Energy comparison drive end vs non-drive end

The non-drive end in the electrical motor must have higher levels of energy because it has less inertia than the side of the motor close to the coupling. It is expected that the variable difference of vibrations (LOR – LR) will be positive since it indicates higher vibrations on the opposite side.

Fig. 10 shows this comparison of energies (LOR vs LOR minus LR):

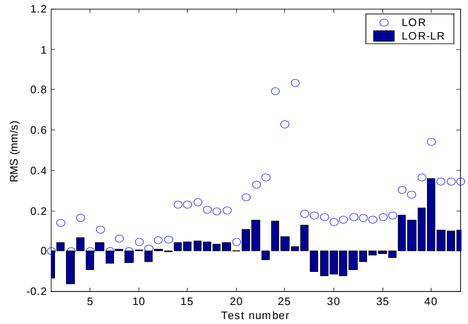

Figure 10

A Kohonen map (6x6 neurons) was trained with these two inputs. Fig. 11 shows the map and two partial maps corresponding to each input.

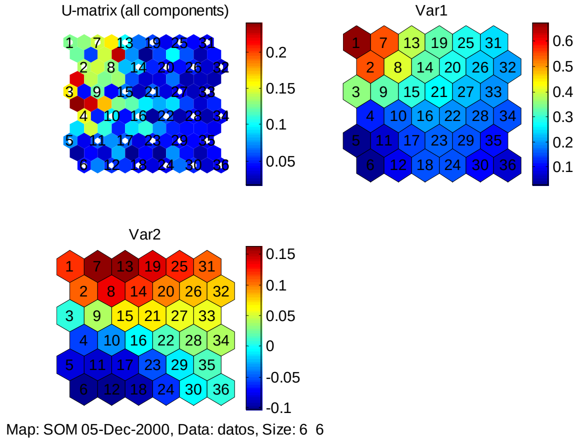

Figure 11

It can be verified that the levels of energy of the opposite side are higher. Furthermore when Var2 (LOR-LR) is negative, it corresponds with the absence of vibrations and when VAR2 is positive, it corresponds with high vibrations, as was to be expected.

The method presented allows the identification of failure modes related to the degradation of bearing at the ends of the electrical motor and, also it can discover if an unbalance in the shaft of the electrical motor is present. Using the self-organising maps presented in Fig. 5 and 6 isolated, bearing degradations can be detected because the maps are reflecting the levels of vibration expected for normal behaviour at different speeds. Comparing both maps at the same time, imbalance of the electrical motor shaft can be detected.

This procedure of fault detection is non-intrusive and allows a quick diagnosis according to the objective of ISPMAT

V. CONCLUSIONS

This paper has described the main features of a software application named “Intelligent System for Predictive Maintenance Applied to Trains” (ISMAPT). Its objective is the monitoring and diagnosis of some components of a type of electrical train named UT450, manufactured by the company ALSTOM and belonging to the Spanish railway company RENFE. One of the components to be monitored by ISPMAT is the electrical motor used for the traction of the train. This paper has paid attention to the monitoring and diagnosis performed by ISPMAT in these electrical motor. The detection of failures has to be done by non-intrusive techniques of measurement and for this reason accelerometers are fixed to the electrical motor. The information that they supply is passed through neural networks based on self-organising maps in order to diagnose the health conditions of the induction motors. The neural networks were previously trained using information of healthy electrical motors at different working conditions. The paper includes examples that demonstrate that the method proposed is useful. More experiments will be done in order to validate this methodology of predictive maintenance to be applied to the UT450 trains.

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