IDENTIFICATION OF DEGRADATION BEHAVIOR ON A RUBBER MATERIAL USING DYNAMIC PARAMETERS AND SELF-ORGANIZED MAPS

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Abstract. *The extended and increasing use of rubber on engineering systems or industrial products, in the last decades, is a fact. Therefore, the products with rubber have a large range of applications in almost any industrial field, e.g. power transmission, oil industry, etc. In the power transmission case, the main function of the rubber is as an electrical insulator. The underground cables are an example where the rubber has an essential importance to guarantee their effective and reliable life time. In the oil industry, rubber could be used in aggressive environments for vibration and noise control or as structural elements. For example, viscoelastic materials are known to act as efficient dampers of structural vibrations, considering their great energy loss hysteresis cycles, which reduce harmful effects of high level vibrations and noise on humans, as well as on machinery. The several environmental conditions around the rubber can induce different kind of degradation processes. Identification and well understanding of these processes constitute a challenge that could reduce the costs of unexpected faults, increasing the reliability of such products. When a degradation process arises, the rubber main properties are modified. Nowadays, in the technical literature available, one can find a large amount of methods that characterize this dynamic behavior which, however, are not related with a degradation process. Hence, the development of methodologies aiming a rapid and precise determination of any degradation process occurring on a particular system is very important. The objective of this paper is to present a new method for the performance characterization and classification of these materials based on behavior parameter, i.e. fundamental frequencies, amplitudes and loss factors, under severe environmental conditions. This would permit to identify degradation processes in course. In order to reach these objectives, the frequency response functions of Oberst beams with a rubber layer (new and degraded) were evaluated (based on ASTM 756-83 specification) and the dynamic parameters were extracted. All data were classified using neural networks based on self-organizing maps, as a way to indentify normal and abnormal "clusters" related with the rubber degradation state. Furthermore, an anomaly detection system was implemented using a MATLAB interface, able to automate and speed up the assessment process. The next step of this work will be the development of an expert diagnostic system in order to determine what kind of degradation process is occurring, according to the information observed and the knowledge available.*

Keywords: *self-organizing maps, neural networks, rubber state, dynamic behavior, Oberst method, anomaly detection.*

1. INTRODUCTION

The extended and increasing use of rubber on engineering systems or industrial products, in the last decades, is a fact. Therefore, the products with rubber have a large range of applications in almost any industrial field, e.g. power transmission, automotive and oil industry, etc. In the power transmission case, the main function of the rubber is as an electrical insulator. The underground cables are an example where the rubber has an essential importance to guarantee their effective and reliable life time. In the automotive and oil industry, rubber could be used in aggressive environments for vibration and noise control or as structural elements. For example, viscoelastic materials are known to act as efficient dampers of structural vibrations, considering their great energy loss hysteresis cycles, which reduce harmful effects of high level vibrations and noise on humans, as well as on machinery. Properties such compressibility, elongation and recoverability from deformation, resulting this great energy loss, make them very efficient materials on vibrations control. The unique physical properties of elastomers are due to the chemical composition of the polymers. The natural elastomers viscoelastic behavior is due to the chemical structures of monomer units used to build them. At the same time, these chemical structures make the polymers vulnerable to thermal and oxidative degradation (Cheng, 2002).

The several environmental conditions around the rubber can induce different kind of degradation processes, since all polymers, and elastomers in particular, are potentially sensitive to the temperatures, fluids, and mechanical conditions. In this way, elastomers could undergo several changes that lead to a failure (Gent, 2001). Moreover, rubber gets aged when used for a long period of time, and usually becomes hardened and with lower damping capacity (Woo and Park, 2011). In both cases, when a degradation process arises, the rubber main properties are modified.

Thereby, the identification and well understanding of these degradation processes constitute a challenge of major importance to the development of techniques that will improve the recognition and classification capacity of rubber components anomalous behavior, while reducing the costs of unexpected faults and increasing the reliability of such products.

Nowadays, in the technical literature available, one can find a large amount of methods that characterize the dynamic behavior (see Section 3), but they are not related with a degradation process [(Budrugeac, 1995), (Brown *et al.*, 2001), (Kannan *et al.*, 2010)]. Hence, the development of methodologies aiming a quickly and precise determination of any degradation process occurring on a particular system is very important. In this sense, various classification methods, such the self-organizing maps (see Section 4), would be used (Russel and Norvig, 2010).

The goal of this paper is to present a new approach for the performance characterization and classification of rubber materials based on behavior parameter (fundamental frequencies, amplitudes and loss factors) and related with their aging and degradation process (under severe environmental conditions). Section 2 gives a diagnostic system structure and describes its basics principles. In order to reach these objectives in Section 3, the frequency response functions of Oberst beams with a rubber layer (new and degraded) were evaluated (based on ASTM 756-83/2004 specification) and the dynamic parameters were extracted. In Section 4 all data were classified using neural networks based on self-organizing maps, as a way to indentify normal and abnormal "clusters" related with the rubber degradation state. Furthermore, an anomaly detection system was implemented (Section 5) using a MATLAB interface, which is able to automate and speed up the assessment process.

2. RUBBER DEGRADATION CLASSIFICATION METHOD

The diagnostic system structure described in Fig. 1 is composed of 4 principal modules. The "Rubber Dynamic Behavior Module" is responsible for the measurement of the dynamic parameters using a characterization process and tools. These parameters are used on the next module ("Automatic Knowledge Extraction") to create the models of behavior classification (normal or abnormal if sufficient information exists). These models will constitute a "Classification Models Data Base" used to detect currents behaviors in the "State Detection" module and distinguish the rubber state. The anomalies detected will be used by the Diagnostic Module to establish rubber condition as normal or abnormal, understanding its level and type of degradation process in course.

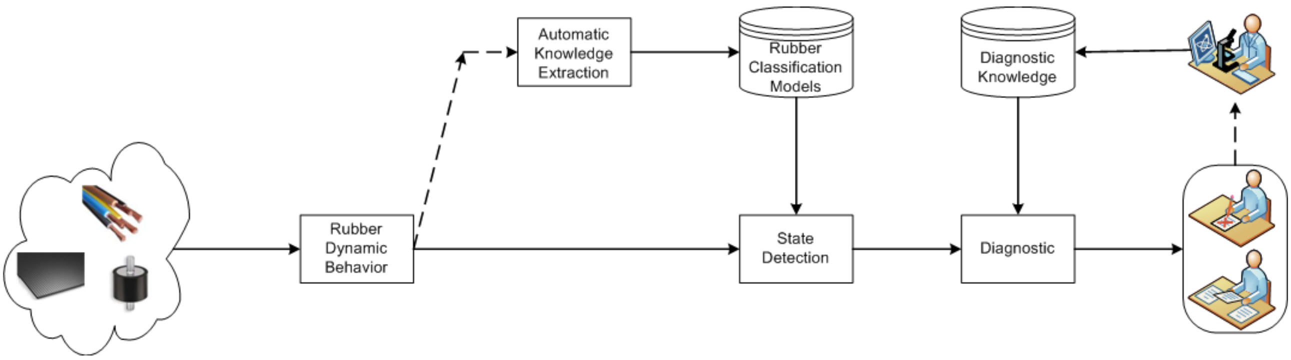

Figure 1. Diagnostic System Structure.

3. RUBBER DYNAMIC BEHAVIOR

First, the characterization of the rubber dynamic behavior is required. In order to do that, methods based on auto-regressive moving averaging models (ARMA), natural excitation technique (NexT), stochastic, etc., are examples proposed to dynamic characterization and modal parameter extraction from output-only data (Auweraer, 2001). Some of them obtain directly these dynamics parameters while others need a couple of stages to extract them from frequency response functions (FRF's).

3.1. Oberst Method and Features Extracting

In this paper, the Oberst Method was chosen to obtain the beams FRF's constituted with rubber layers. Figure 2.a shows the "Oberst Apparatus" (Complex Modulus Apparatus B&K Type 3930) which consists in a test jig with a guide pillar and two adjustable supports for the transducers. The main clamping arrangement for the sample bars is located at the top of the apparatus. Two magnetic transducers B&K Type MM 0002 with sensibility of 50 mV/m/s were used. The transducer mounted at the highest position excited the beam, while the other transducer measured the response. A "Hanning Window" was applied to both signals. FRFs were generated (based on ASTM 756-83 specification) by a

B&K Pulse analyzer IDAe frame type 3560C, 4/2 I/O module Type 3109, using the Fast Fourier Transform (FFT) algorithm. The frequency spectrum was then processed using the LMS TestLab commercial software, and the corresponding mode-shapes and loss factors were obtained. Fig. 2.b presents the used beam configuration.

(a)

(b)

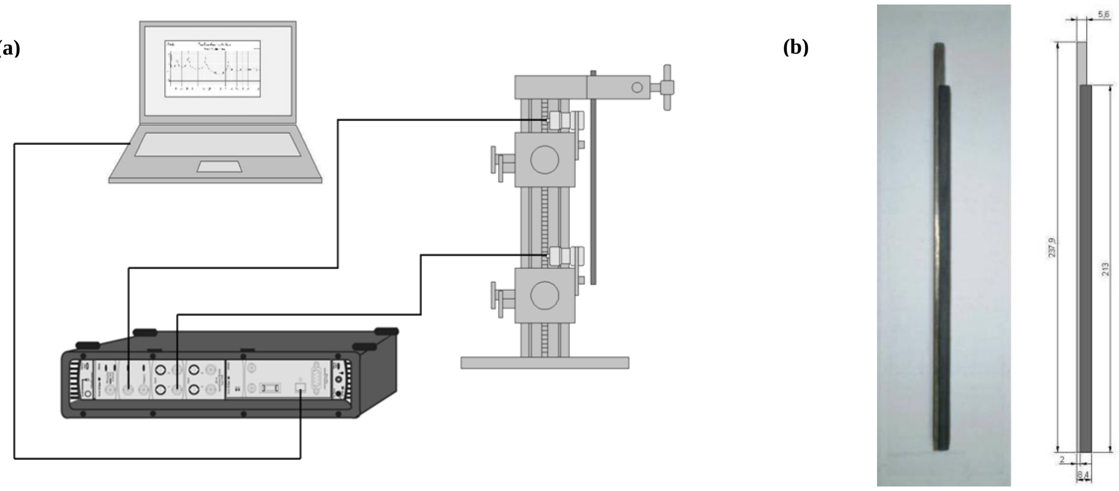

Figure 2. (a) Schematic representation of the acquisition system with the Complex Modulus Apparatus B&K Type 3930 (Oberst Apparatus), B&K Pulse analyzer type 3560C and a computer. (b) Oberst Beam.

Rubber samples in four different states of theirs life-cycles (between new and completely degraded) were used in the experimental process. Table 1 shows the main description of all analyzed rubber samples.

Table 1. Rubber Samples Description.

Type	Material Code	Description
1	MAT_0	Beam with a “Completely Degraded” rubber sample
2	MAT_1	Beam with a “New” rubber sample
3	MAT_2	Beam with a “Humid Partial Degraded” rubber sample
4	MAT_3	Beam with a “Dry Partial Degraded” rubber sample

All the degradation process was made submerging the samples in an organic solvent. The FFT was obtained for the frequency spam between 0 and 3200 Hz, using 300 averages for each measurement.

3.2. Dynamic Parameters

For each material type, a set of 18 FRF’s was obtained. Figure 3 shows an example of a measured FRF and its coherence.

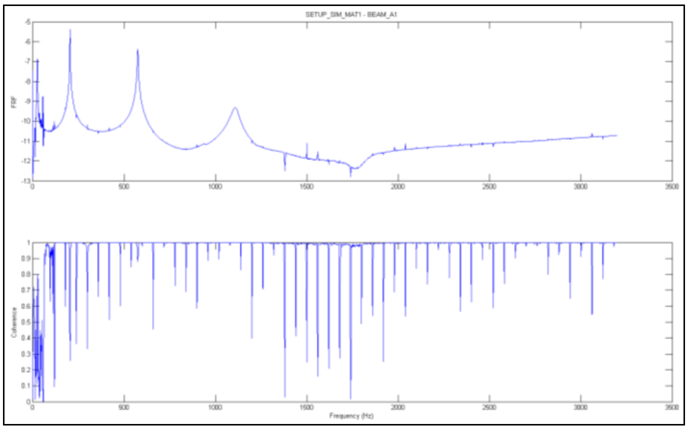

Figure 3. Example of measured FRF and its Coerence.

Figures 4.a and 4.b show all the measured FRF’s corresponding to new rubber, i.e. a rubber without use, and to completely degraded rubber, respectively. Comparing these two figures, it is clear not only that the degradation process changes the rubber dynamic behavior, but also that it is difficult to distinguish what dynamic parameters are well related with this ageing process.

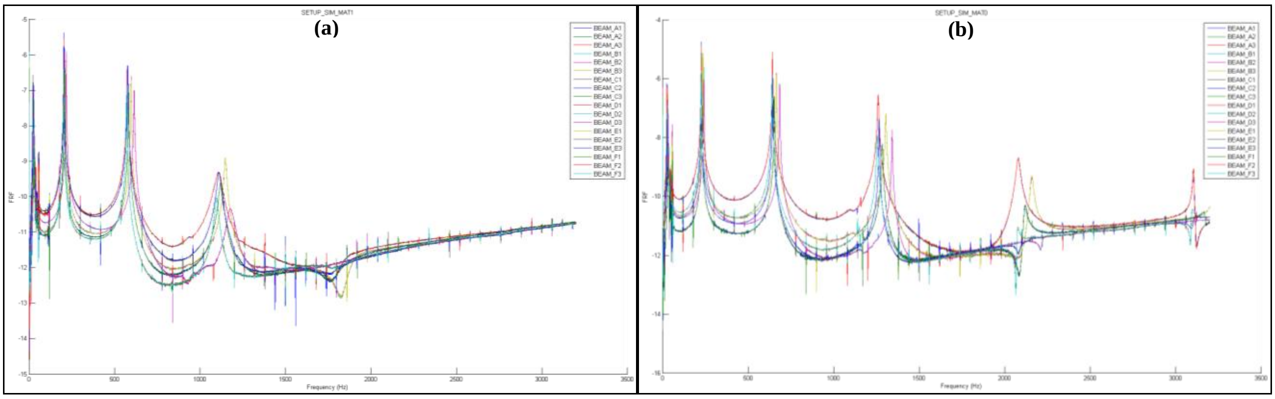

Figure 4. All FRF´s obtained to (a) MAT_1 (Type 2 – "New" Rubber) and (b) MAT_0 (Type 1 - "Degraded" Rubber).

Measurement data of rubber types 1, 2 and 3 (Case 1), and 1, 2 and 4 (Case 2) are shown in Figures 5 and 6, respectively. In these two cases a visual classification and differentiation from the 3 rubber types is more difficult and could takes so much time a decision. These problems are especially observed for the dry partial degraded rubber samples (Mat_3) used in Case 2.

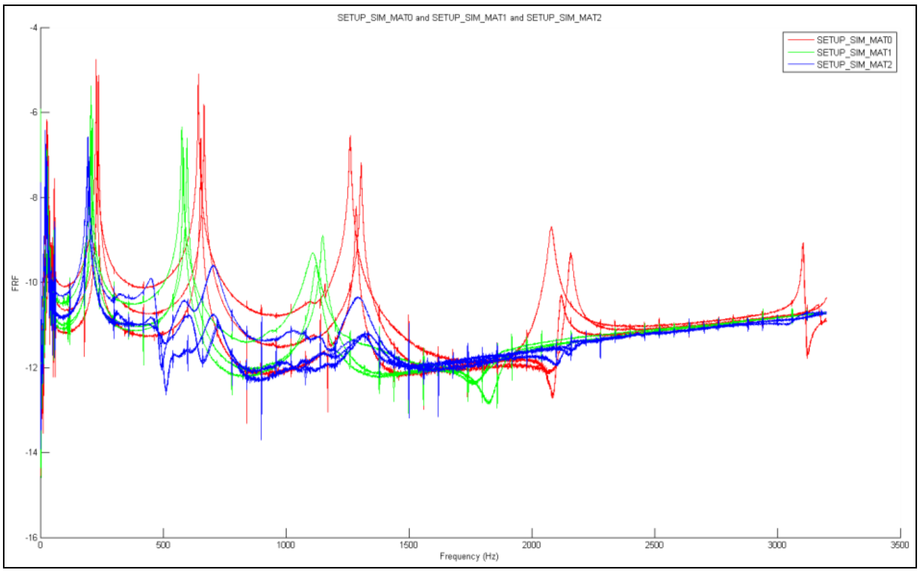

Figure 5. FRF's of 3 rubber degraded states 1-2-3.

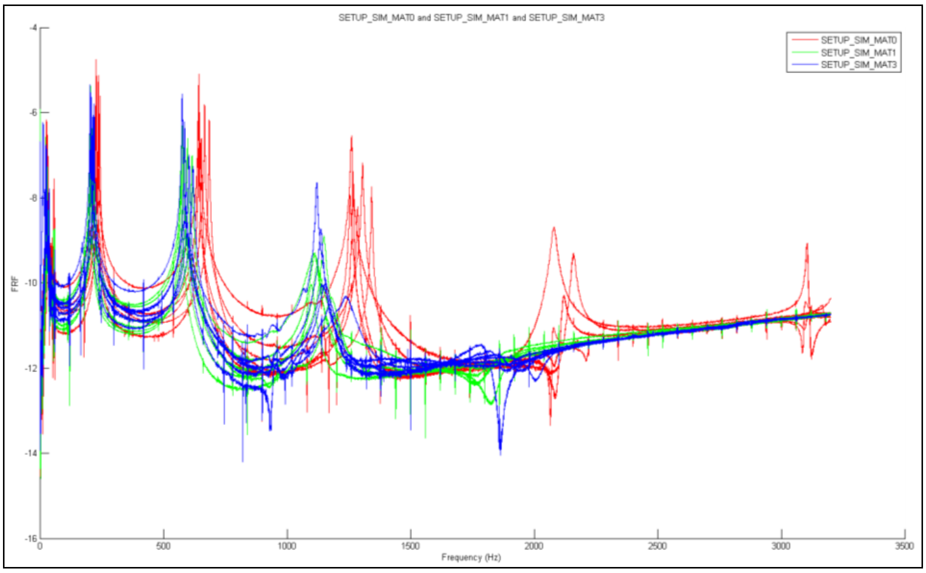

Figure 6. FRF's of 3 rubber degraded states 1-2-4.

The extracted parameters of the FRF's data were the amplitudes, frequencies and loss factors at three first resonance peaks that together with the difference between the resonance frequencies 2 and 1, and between the resonance frequencies 3 and 2, were used to build classification models based on automatic knowledge extraction.

4. RUBBER CLASSIFICATION MODELS

Techniques such as Decision Trees (Russel and Norvig, 2010), Rough Sets (Shen *et al*, 2000), Self-Organizing Maps – SOM (Kohonen *et al*, 1996), etc. are widely applied in engineering classification problems. Self-organizing maps are unsupervised neural networks able to obtain excellent clustering results. In addition, an easy evaluation of the result is possible through the graphical representation on maps whose different labels can be grouped by visual inspection. (Verdu *et al*, 2006). Applying some index functions, it is possible to obtain an optimum clustering, but some "supervision" is necessary to filter the results of the maps (i.e., the operator selects the maximum number of clusters).

As known, the Kohonen self-organizing maps (SOM) are neural network models that map multi-dimensional input data into a low-dimensional space represented by the number of neurons (Kohonen et al, 1996). It is a powerful tool for high-dimensional data compression and visualization (Astel et al, 2007).

The SOM is defined by a set of patterns (weights of the map) that cover the input space in such a way that the distribution of input data is approximated by the distribution of the patterns or neuron weights. The values of the patterns are adjusted during the network training phase using an unsupervised learning algorithm. More in detail, at the iteration t of the training algorithm, the input vector x_t is closest and assigned to the pattern C_j to which it has minimum distance:

$$j = i(x_t) \triangleq \arg\min_i d\big(x_t, C_i(t)\big) \tag{1}$$

Then, the SOM updates the position of the patterns that are inside the neighborhood region of C_j, as follows:

$$\begin{aligned} &C_i(t+1) = C_i(t) + \gamma(t)[x_t - C_i(t)] \quad \text{if } i \in N_j(t) \\ &C_i(t+1) = C_i(t) \quad \text{if } i \notin N_j(t) \end{aligned} \tag{2}$$

, where $\gamma(t)$ is a monotonically decreasing function of time with values between 0 and 1. The neighborhood region $N_j(t)$ of a weight C_j is defined as the region of the map where patterns have distance smaller than or equal to a specified radius from C_j. It is clear that the training algorithm requires the definition of a distance measure d between cases and patterns. It is a general fact that given the probability distribution $p(x)$ of the input data, the Kohonen algorithm minimizes an average expected quantization error function E given by Eq (3),

$$E = \int f\Big(d\big(x, C_j\big)\Big) p(x)\, dx \tag{3}$$

, where C_j is the pattern associated to the input vector x.

The result is that input data showing similar characteristics among them, are clustered together and a representative pattern is assigned to each cluster. Thus, data are represented by a finite set of patterns, which are the centers of the clusters found by the training algorithm. Furthermore, it is a general fact that the SOM training algorithm adjusts the map weights in such a way that patterns will be more concentrated in those areas of the input space with higher density. Each pattern is graphically represented as a neuron and the map is represented in a lower-dimensional space as a set of neurons. Each neuron contains all the input data that are represented by the corresponding pattern and neurons that are close each to the neighbor one in the map typically show close patterns.

It can be said that the transformation that SOM performs is a non uniform quantization of the input space (Sun, 2000). The advantages of SOM algorithm are its classification and visualization abilities for large environmental data sets. SOM results allowed detecting natural clusters and identifying important discriminant variables responsible for the clustering (Astel *et al*, 2007).

Thereby, all data were classified using neural networks based on self-organizing maps, as a way to identify normal and abnormal behaviors related with the rubber degradation state. Firstly, for Case 1, a scatter plot analysis is presented on Fig. 7 in order to identify some relationships between the variables analyzed and the rubber classification. These relationships are obvious for some variables (for example loss factor of the resonance peak 3 and frequency of the resonance peak 1), but unclear for others. In this situation a combined set of variables should be used for a better classification. Also, the scatter plot is helpful to well understand and identify the independent variables. The same analysis was carried out for Case 2, but in this case it was more complicated to indentify variables able to classify the different rubbers. Furthermore, Case 2 had less independent variables, i.e. many variables "explain" the same knowledge about the rubber classification.

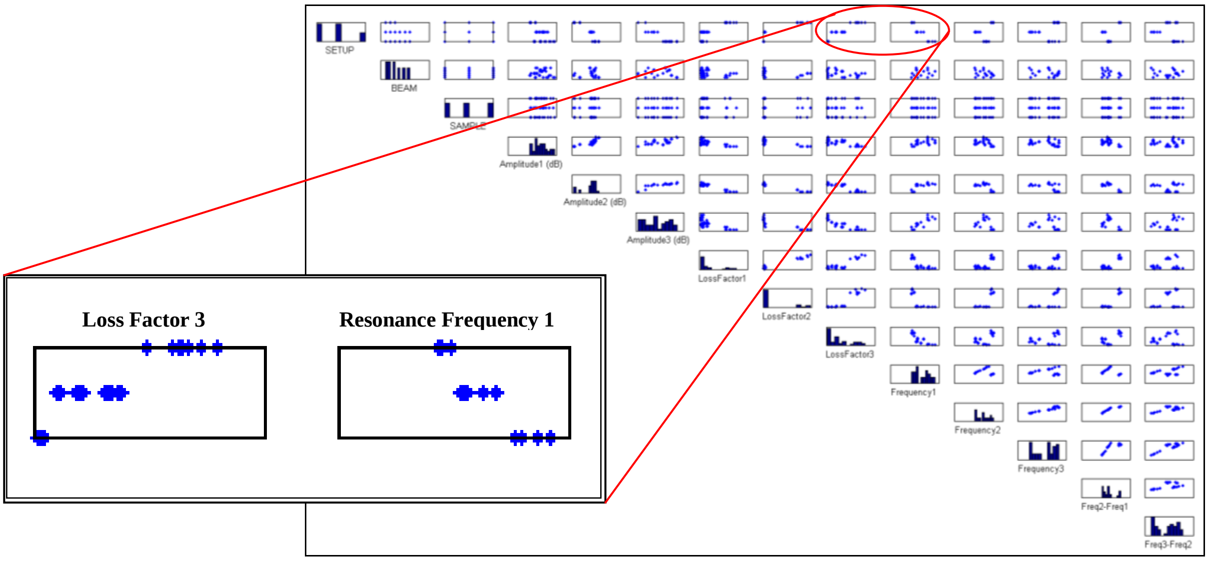

Figure 7. Scatter plot to Case 1 data.

Thus, both for Case 1 and Case 2 analysis, two main different models were created. One of them is using all the available variables (full model) and another one with the minimum possible number of variables (reduced model) able to classify the different rubbers degradation states. The reduced model was obtained after a large attempts and tests with many sets and numbers of variables. Fig. 8 presents the "weights" of the full model used in case 1. Black color means the high values and yellow low values of "weights" to all neurons in the map.

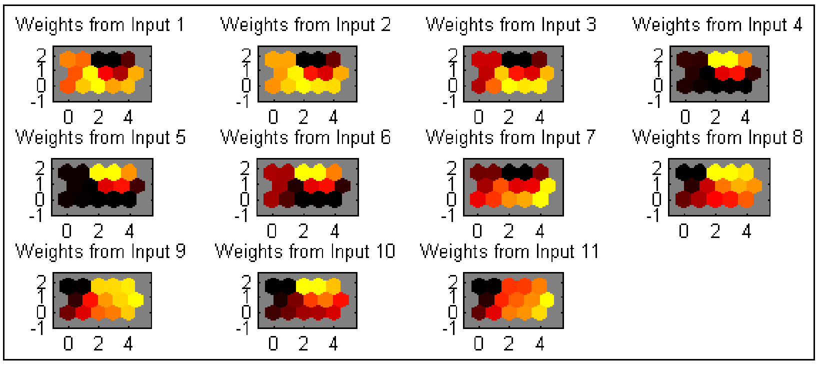

Figure 8. Case 1 full model weights.

Using training and validation data the full model was created (Fig. 9) and as a result three classification groups were identified. The "numbers" inside de neurons represents the numbers of test hits assigned to these neurons during the model validation, last part of the training process. Here, in SOM label assignation, black color means that these neurons are empty i.e. no data were identified with this state.

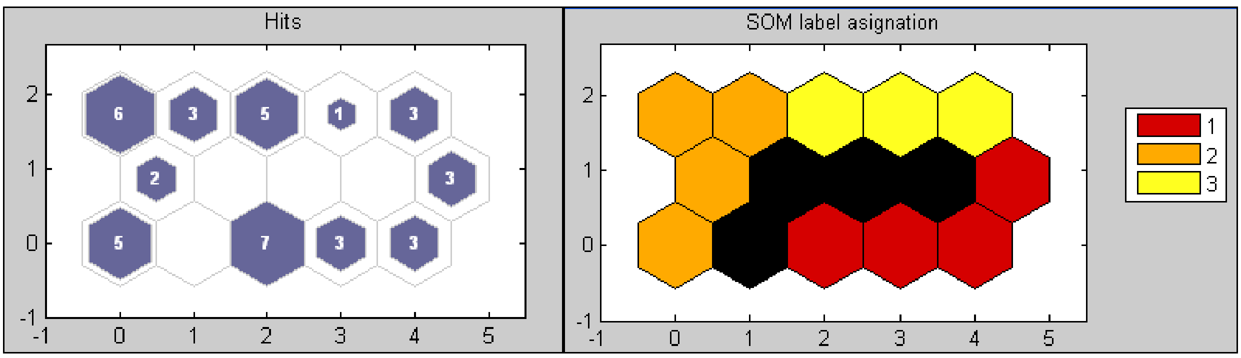

Figure 9. Case 1 full model classification.
(1 - Mat_0 / 2 - Mat_1 / 3 - Mat_2)

Some "weights" in Fig. 8 have the same contribution to the variables classification. A reduced model is proposed using such input variables only the Amplitude of resonance peak 1 and 2, the loss factor of resonance peak 3 and the resonance frequency of peak 1. Reduced model "weights" and classification are presented in Fig. 10.

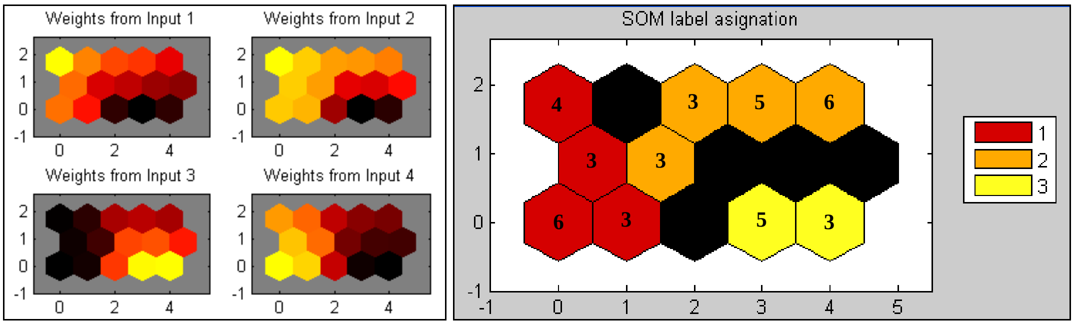

Figure 10. Case 1 reduced model weights and classification.
(1 - Mat_0 / 2 - Mat_1 / 3 - Mat_2)

To each classification group (1 - Mat_0 / 2 - Mat_1 / 3 - Mat_2) was identified and assigned a numbers of patterns (by neurons) which contain similar dynamics characteristics. Figure 11 shows the mean pattern for the 3 groups of Case 1. When a new input data is analyzed with this map (model), the distance between the patterns "weights" and the new data are evaluated. The classification is carried out identifying the nearest pattern and assigning his label for the input data.

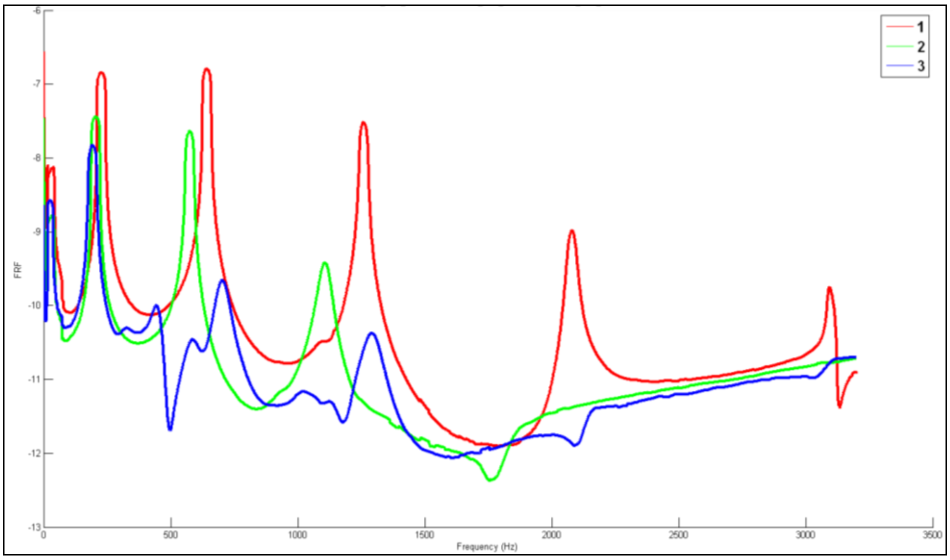

Figure 11. Case 1 reduced model – Map Patterns (mean by classification group).

The same analysis was carried out for Case 2. Fig. 12 and 13 show the full and reduced model "weights" and classification, respectively. In both models the area (neurons) occupied by the new rubber (Mat_1) and the partial degraded rubber (Mat_3) are little mixed. This kind of classification maps means that the differences between them are not big enough i.e. the degradation process did not really change the dynamics parameters.

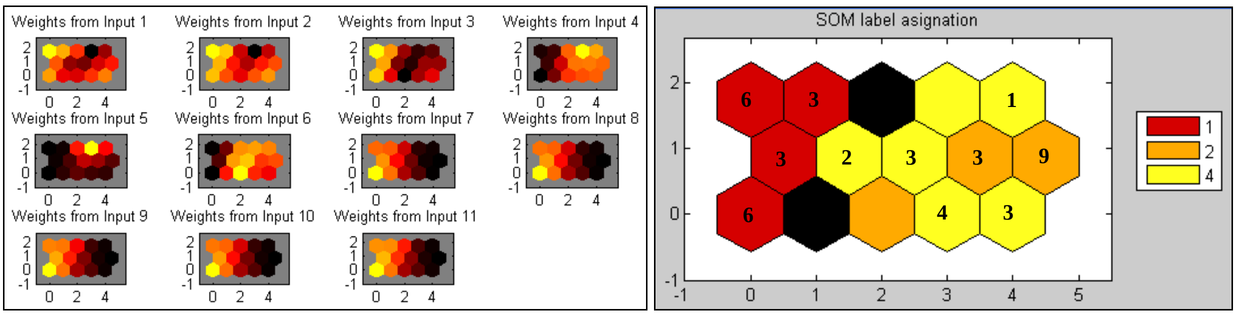

Figure 12. Case 2 full model weights and classification.
(1 - Mat_0 / 2 - Mat_1 / 4 - Mat_3)

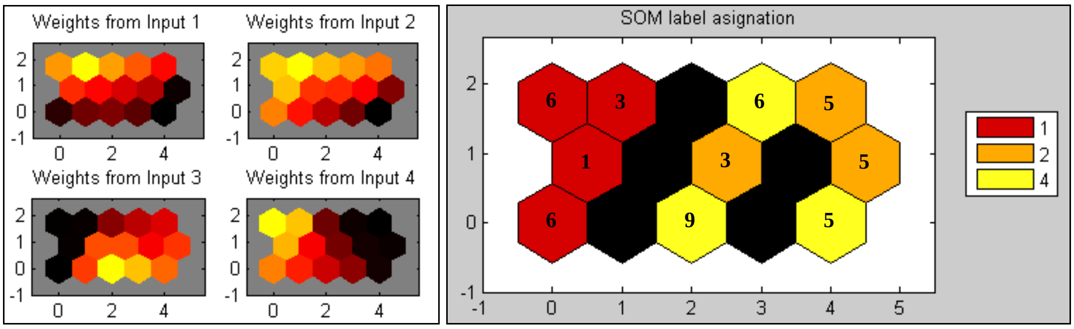

Figure 13. Case 2 reduced model weights and classification.
(1 - Mat_0 / 2 - Mat_1 / 4 - Mat_3)

In Case 2 (Fig. 14) the pattern differentiation, and consequently the map (model) classification, was not so clear such in Case 1 because the dynamics characteristics of the rubber samples type 2 and type 4 are very similar.

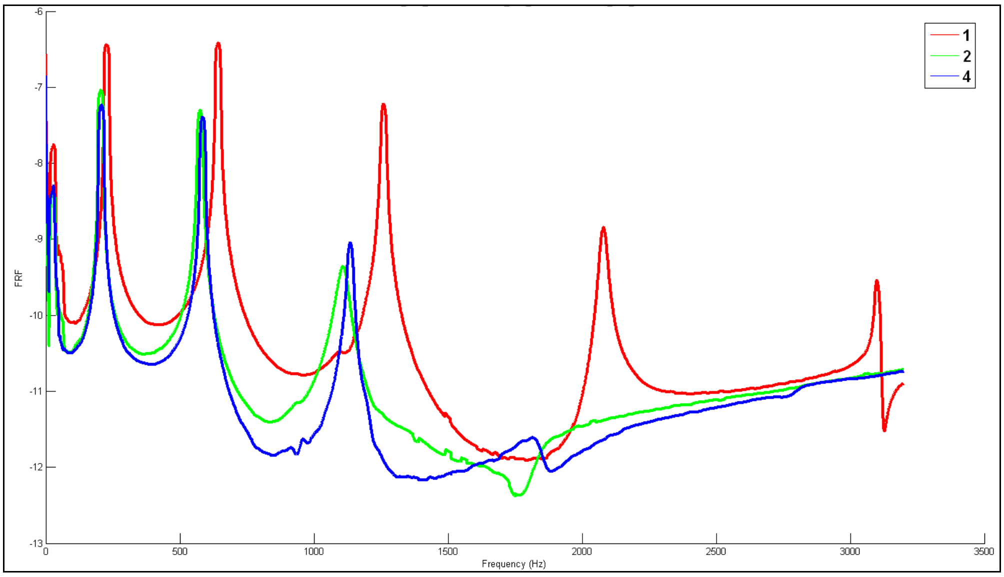

Figure 14. Case 2 reduced model – Map Patterns (mean by classification group).

5. ANOMALY DETECTION

An anomaly or degradation detection system was implemented using a MATLAB interface. This is able to automate and speed up the assessment process. Figure 15 shows the result of a test carried out with both cases data and the anomaly detection uncertain is presented in Table 2. In both cases were used the reduced model.

Table 2. Anomaly detection uncertainty by neuron

Case	**Neuron Uncertain**														
	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**	**15**
1	0	0	NaN	0	0	0	0	NaN	NaN	NaN	0	NaN	0	0	0
2	0	NaN	0.33	NaN	0	0	NaN	0	NaN	0	0	0	NaN	0	0

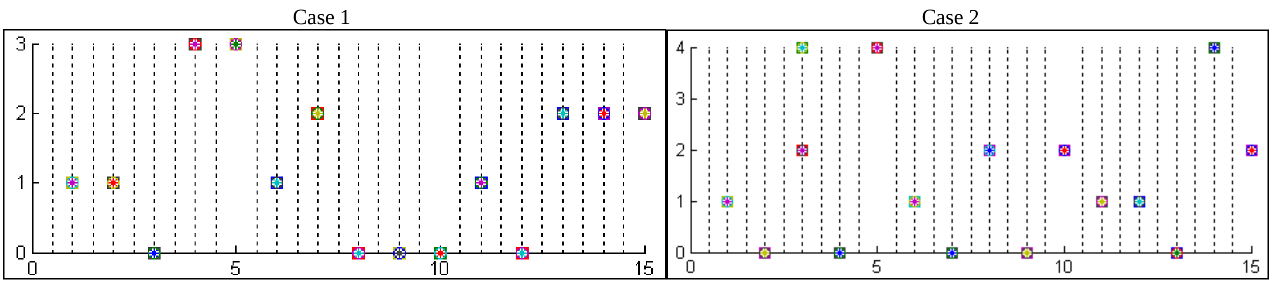

Figure 15. Classification and anomaly detection by neuron.

In Case 1 the anomaly detection did not make mistakes and the uncertain level by neuron in the map was zero. In Case 2 the neuron three uncertain levels was 0.33 meaning that this neuron had committed a 33% error classification. These different uncertain levels between Case 1 and 2 are expected and justify by the not really clear pattern differentiation between the dynamics characteristics of the rubber samples type 2 and 4.

6. CONCLUSIONS

A new anomaly detection method based on a SOM neural network has been presented in order to classify different degradation conditions of rubber materials. The anomaly detection method provides the effective detection of degradations based on a model classification knowledge. Some anomaly detection uncertainty appears for Case 2. In both cases is not necessary to use all parameters available (full model) i.e. only the resonance peak amplitude 1 and 2, the resonance peak loss factor 3 and the resonance peak frequency 1 (reduced model) are enough.

The method presented here can effectively identify rubber degradation processes in course. This is the first step to create an expert diagnostic system. The future research activity, already under study, is devoted to achieve two objectives: the development of an expert diagnostic system in order to determine what kind of degradation process is occurring according to the information observed and the knowledge available, and the study of the potential and applicability of other promising clustering techniques.

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