Artificial neural networks for pattern recognition in oil rod pump system anomalies

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Abstract - *The present paper shows the development of an Artificial Neural Network system for Downhole Dynamometer Card pattern recognition in oil well rod pump systems. Dynamometer Cards are the main diagnostic measure tool in Rod Pump System, which is the most popular elevation mechanism used in the oil industry. Here it is covered the establishment of pattern classes and a set of standards for training and validation, the study of descriptors which allow the design and the implementation of features extractor, training, analysis and finally the validation and performance test with a real data base. It is shown that the use of artificial neural networks in order to analyze the pump mechanic system in oil elevation is feasible.*

Keywords: *Artificial neural network, pattern recognition, oil well rod pump, dynamometer cards.*

1 INTRODUCTION

Oil is one of the main assets in the world economy and certainly one of the most valuable raw material resources of the planet. The oil reserves are found in the subsoil and only rarely it has energy to reach the Earth surface naturally. Normally it is necessary to raise the oil artificially in order to get it.

The most popular elevation mechanism used in the oil industry is the “Rod Pump System”, which is basically composed by three elements: the “Pumping Unit”; the “Sucker Rod” and the “Pump” itself. The main diagnostic measure tool is the “Downhole Dynamometer Card” which is formed by the values of position of the pumping unit and the pressure in the connection junction of the sucker rod and the pump.

The use of an automatic system for pattern recognition of downhole dynamometer cards allows anticipating the problems with its earlier identification and therefore to take both corrective and prevention measures for it. This will bring direct impact in:

- either increasing or maintaining the oil production level;
- reduction on the energy that is spent;
- increasing the equipment availability.

Several works have appeared about mechanisms of automatic classification of downhole dynamometer cards. However, their results either are limited to a reduced number of the anomalies or have low performance. [1, 2, 5, 6, 7, 8, 9, 12, 16, 17, 18].

The present work proposes to investigate in the literature a set of classes of anomalies of downhole dynamometer cards, to artificially generate one data training set, to study the feature extractor’s mechanisms, to implement and train Artificial Neural Networks (ANN) for recognizing these patterns. Finally, it also proposes to test the result with cards obtained from real rod pump system systems.

2 THE PUMP SYSTEM

The main components of the system, which are shown in Figure 1, are: the pumping unit; the sucker rod; and the pump itself.

The pumping unit is normally connected to an electrical engine or an internal combustion engine through a gearbox of torque transmission which transform the spinning movement of the engine into an alternate movement at the top of the sucker rod. The sucker rod on its hand transmits the mechanical energy received at the surface to the pump. Some energy is lost in friction during this process.

Finally, the pump, which is shown in details at Figure 2, transmits the mechanical energy received to the polyphasic fluid (oil, gas, sediments and water).

The main components of the pump are the plunger, the barrel and the traveling valve and the standing valve. They together form the pump system of a positive displacement pump type.

In the downward course the traveling valve opens and the standing valve shuts. In this way the weight of the fluid column is supported by the sub-set of the standing valve and it is transmitted by to the tubing though the barrel. The plunger’s interior is flooded by the fluid. Plunging the column of rods in the fluid causes a small production due to the volume which was shifted.

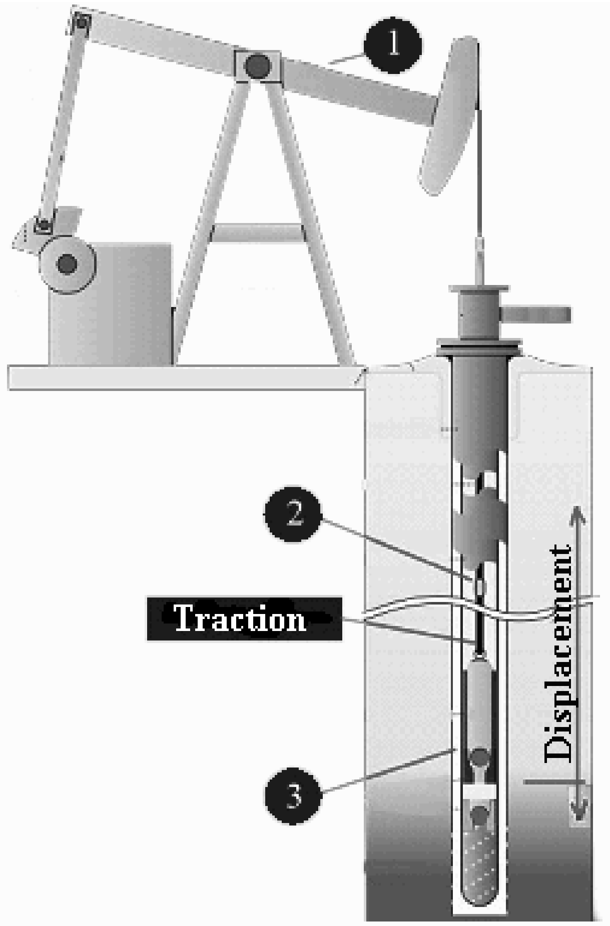


Figure 1. The Pump Mechanical System.

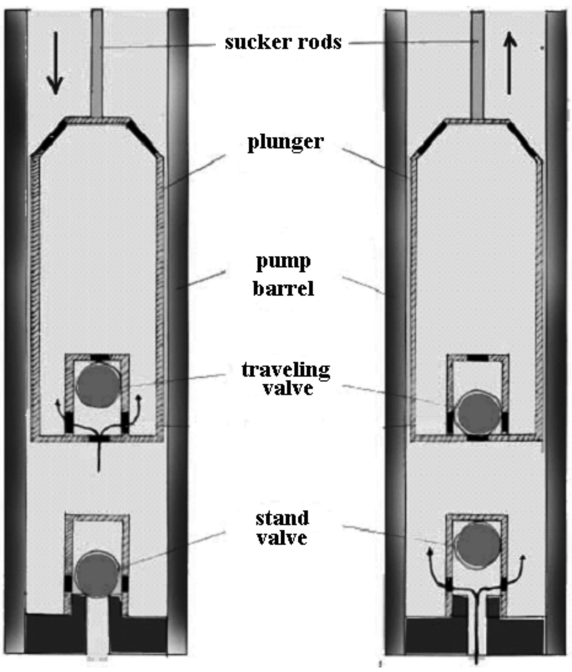
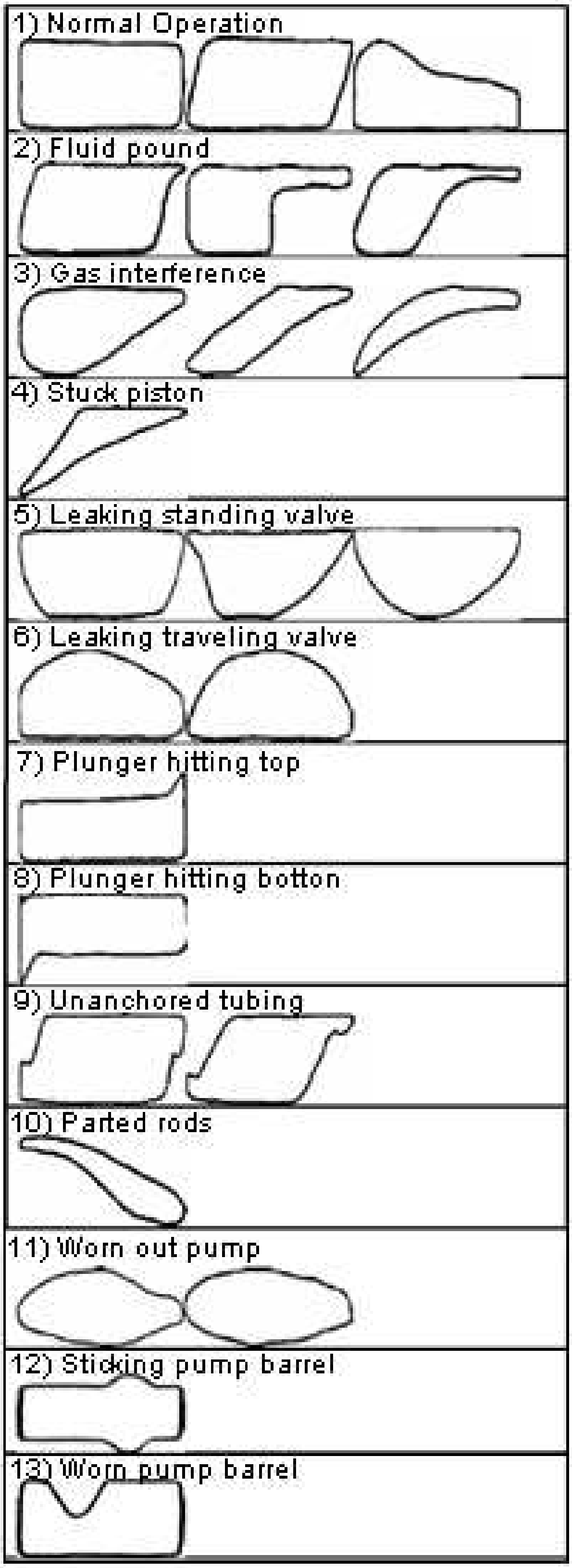


Figure 2. The pump.

Table 1. Classes for downhole dynamometer cards.



In the upward course the traveling valve shuts and the standing valve opens. The fluid shifted by the plunger shows up at the surface whereas the barrel is refilled through the standing valve. In this way, the weight of the fluid in the tubing is transmitted to the columns of rods.

The dynamics described here can be seen as a simple harmonic motion of a mass corresponding to the columns of rods and the fluid load accumulated at a single point.

That approach is no longer true if, for example, the depth increases; or, if the fluid load increases; or, if either the friction or the rotation rises; or, if the physical properties of the equipments change. These cases require a more accurate study on the operational conditions and this leads to solving damping wave equations to describe the motion.

Barreto Filho presents in [3] a detailed study on the rod pump system and proposes an algorithm to compute the mechanical strengths on the sub-surface (at the bottom) from measurements conducted on the surface.

2.1 Monitoring the System

The periodic evaluation of the system is done through [4]:

a) Plunging the pump: determined by the level of the dynamic level, which corresponds to the height of the fluid above it during production (Sonolog register).

b) Downhole dynamometer card: obtained by the readings of the rod displacement and its corresponding traction force.

c) Other indicators obtained through production tests, or verifying the temperature of the rods, or also pressurization tests of the equipment.

2.2 The Downhole Dynamometer Card

The downhole dynamometer card is the main tool, and also the richest device, for monitoring the system. It was created in 1936 when Walton E. Gilbert published his work [14] that describes the its use for diagnosing the rod pump system.

Actually the device created by Gilbert was set up just above the pump on the sub-surface, which somehow restricted the technical application.

As a matter of fact the paper establishes graphic forms of the dynamometer cards associated to the system's anomalies.

To better diagnose the working conditions of the rod pump system several papers have appeared later, pointing out to the pioneer work of Gibbs [13] that used mathematical modeling and computer techniques to determine the conditions on the sub-surface from measurements conducted on the surface.

Eickmeier in [10] presents the Delta II dynamometer and its corresponding data analysis. Electronic sensors arranged as a load cell and a potentiometer are used together with analogical recording.

Several schemes have been done in order to get an automatic diagnostic for the downhole dynamometer cards using both statistical and syntactic methods, artificial neural networks (ANN), or even symbolic neural networks [5]. By doing a bibliographic search one can establish a wide set of classes that are used for pattern recognition of the downhole dynamometer card behavior (Table 1).

3 METHODOLOGY

3.1 Pattern Recognition

The proposed process for pattern recognition of an occurrence has two stages: The first stage is the data acquisition, which is presently accomplished by field instrumentation and its corresponding processing (Figure 3), where a computational solution for the model, as described in section 2.3, transforms a surface dynamometer card, which is formed by values of displacement and tension of the rods acquired by using sensors that are placed on the surface equipment, into a downhole dynamometer card, which is also a set of displacement and tension values, but, however, conceived for the position corresponding to the junction between the column of rods and the plunger.

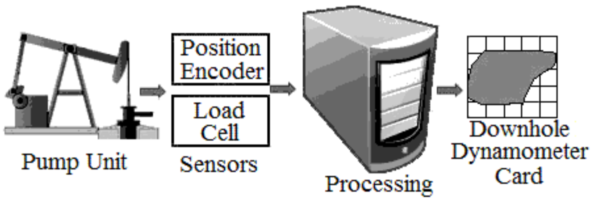


Figure 3. Data acquisition and signal processing.

At this point, since the downhole dynamometer cards from different wells have some variation interval between rod tensions and also some different displacements, there is a need for normalizing the values.

The second stage the tool for pattern recognition itself (Figure 4), which has two parts [11]:

1st) the feature extraction, which does the a transformation of the vector X from an observation space of dimension 'm', which is the downhole dynamometer cards data, into the characteristic space of dimension 'q', where q < m, in order to simplify the classification task.

2nd) the classifier, comprised of a ANN that associates the vector of characteristics Y of dimension 'q' into one of the classes of the decision space which has dimension 'r'.

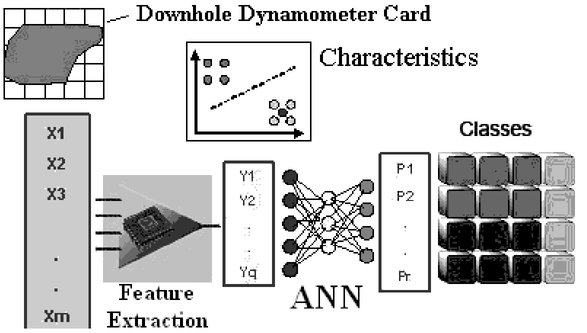


Figure 4. Characteristic Extractor and Classifier (ANN).

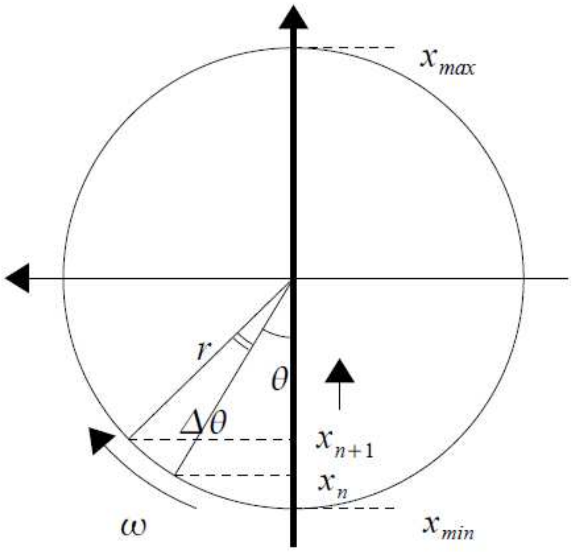


Figure 5. Simplified model.

3.2 Characteristic Extractor

The Characteristic Extractor has two approaches [15], the first being to eliminate the redundant information and the second being the linear or nonlinear transformation into the observation space dimension.
There are some factors that make the design of the Characteristic Extractor easier:

a) The downhole dynamometer cards are not subject to rotation and therefore, one can use histograms to extract characteristics.

b) The downhole dynamometer cards have a borderline which is closed and periodic, one can use Fourier descriptors here.

c) The data normalization process eliminates the translation and scale effects.

d) There is no overlap of other signals which might interfere with data.

3.3 Classifier

Here, the proposed scheme is a multiple layers feed forward ANN with a supervised training device [11].

3.4 Training and Tests

As for the training the proposed structure is to generate artificially a set of standards using the class models as shown in Table 1, with a random noise introduced. One has to be aware of generating the same number of standards for each type of class.
In this way, with a typical image of a normalized downhole dynamometer cards, the pair of values, position and traction are obtained.
In order to have an approximation closer to reality, where the values of the cards are attained by sampling in regular time intervals, a simplification was conducted, where the sucker rod motion is the vertical projection of a point in simple harmonic motion (Figure 5) with a constant angular velocity.
Assuming that a complete period N samples are introduced; one has that, for the n^{th} sample:

$$x_n = x_{min} + r\big(1 - cos(\theta)\big)$$

where

$$r = \frac{(x_{max} - x_{min})}{2}$$

$$\theta = n.\Delta\theta$$

$$\Delta\theta = \frac{2\pi}{N}$$

It is interesting to notice that the variation rate of the position of the samples with respect to the variation angle can be expressed by:

$$\frac{\partial x}{\partial \theta} = rsin(\theta)$$

This gives a small variation in the position of the samples at the beginning and at the end of the ascending and descending courses (x_{nin} and x_{max}) that reflects in a more detailed view. Here it is used N ? 100 for the forward angle Δθ = 0.0628 rd, or 3.6º.

4 RESULTS AND DISCUSSION

Initially, an application was done with the aim of using the proposed methodology to a set of 6,101 cards from real oil wells and each one composed of a set of 100 points, which were previously classified by a human expert.

a) Normal operation = 1843.
b) Fluid pound = 4123.
c) Gas Interference = 15.
d) Leaking standing valve = 78.
e) Plunger hitting top = 42.

4.1 Set of Artificial Standards

The first step to obtain the artificial standards was to generate an image set in bit map, based on models, and using image manipulation software (Photoshop ver. 8.0.1). Figure 6 illustrate a set of 4 images that represents the class of cards with fluid pound and in situations ranging from small to large gravity.

A set of 100 points was obtained from each image. These points are arranged in values of position (x axis) and traction (y axis), where half of them establishes the ascending curve of the pump whereas the other half forms the descending curve of the pump.

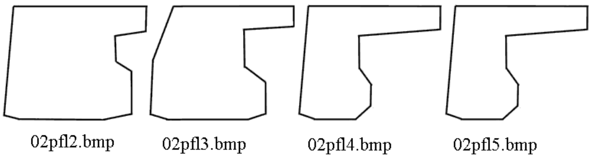


Figure 6. Bit maps from some fluid pound models.

These sets have been normalized:

$$x_{norm} = \frac{(x - x_{min})}{(x_{max} - x_{min})}$$

$$y_{norm} = \frac{(y - y_{min})}{(y_{max} - y_{min})}$$

After normalization a white noise was added to the x axis. Since these values, after being added by noise, can go over the unit, they have to undergo to a second normalization. Figure 7 shows the overlapping of 300 artificial downhole dynamometer cards.

On the other hand Figure 8 shows a comparison between the distances of successive x axis of points obtained artificially (Figure 8a) and from real cards (Figure 8b). The graph shows the form

$$\Delta x \epsilon [-\Delta x_{max}, +\Delta x_{max}]$$

as a function of the position x_n on a complete period ($n \in [1 , 100]$). One can observe that the minimal variation occurs on the limits of the periodic motion (around n = 1, n = 50 and n = 100) whereas the maximum variation occurs on the intermediate points (around n = 25 and n = 75).

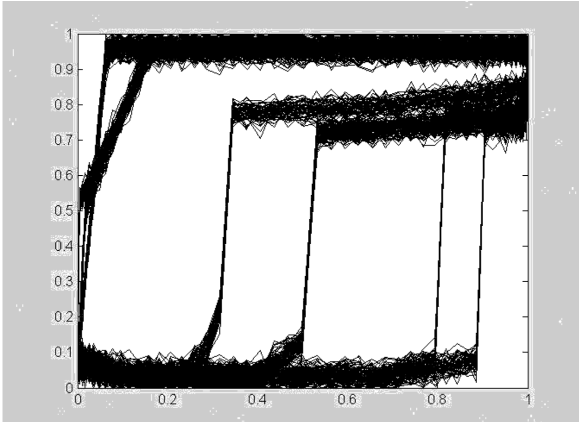


Figure 7. Set of artificial standards for cards with fluid pound.

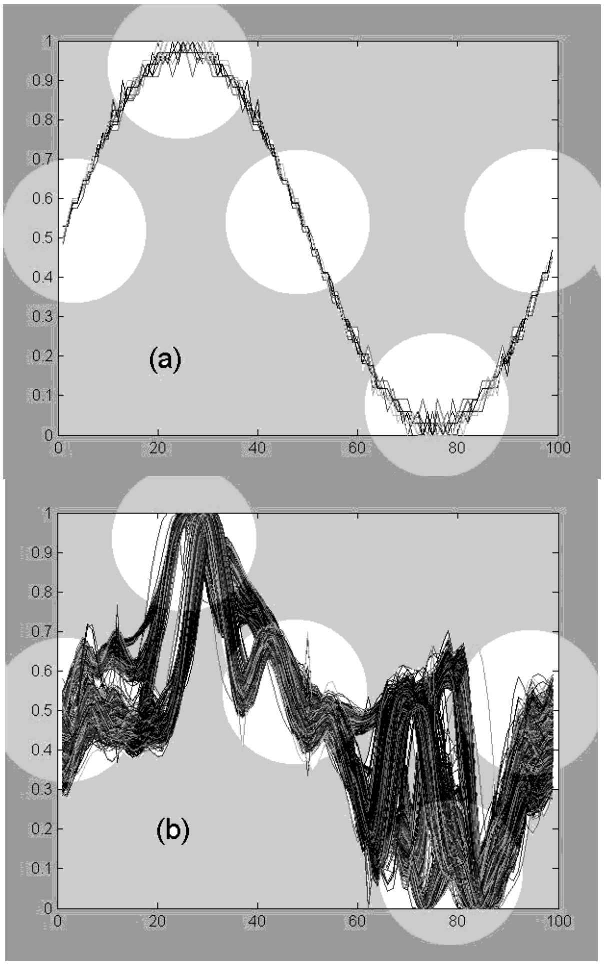


Figure 8. Distances between successive x axis.

By using these techniques two sets of artificial cards were generated: one for the training of the network and another one for the validation. Each of these sets consists in 8 different classes with 300 downhole dynamometer artificial cards by each class. These 8 classes are a subset of the ones shown in Table 1:

normal operation, fluid pound, gas interference, stuck piston, leaking standing valve, leaking traveling valve, plunger hitting top and plunger hitting bottom.

4.2 Characteristic Extractor

Here a characteristic extractor that uses vertical projections of the ascending and descending curves was used. This is shown in Figure 9. Acceptable results were obtained with a set of 16 projections of the descending curve and also 16 projections of the ascending curve.

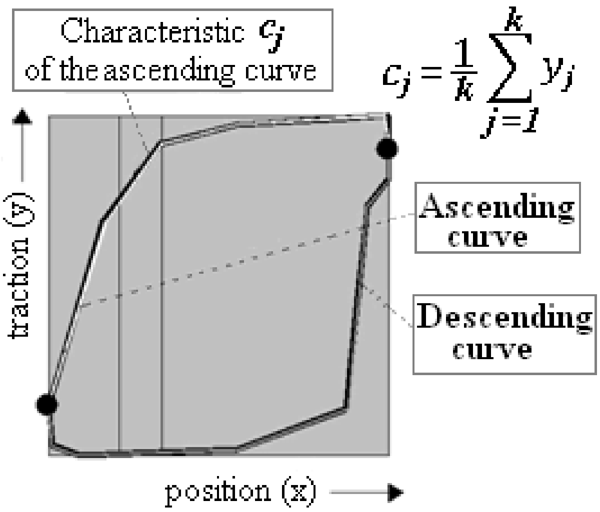


Figure 9. Characteristic extractor.

This allowed a reduction of the dimension of the space from 200 (corresponding to 100 pairs of values of potion and traction) to just 32.
Figure 10 shows the output of the 32 outcomes from the plunger hitting top for the several families of artificial downhole dynamometer cards.

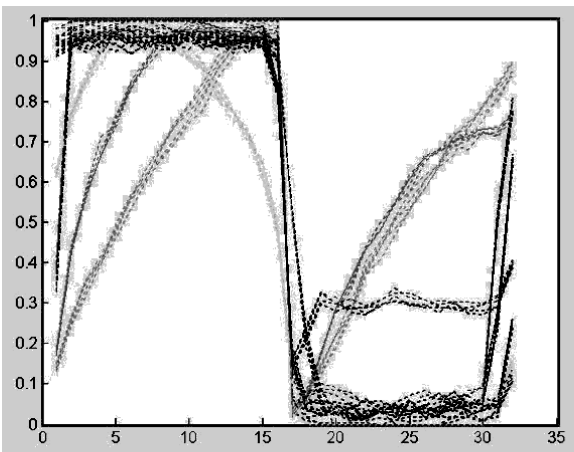


Figure 10. Output of the characteristic extractor.

One can verify that each family of artificial downhole dynamometer cards holds a well-defined recognizable signature.

4.3 Classifier Results

Several tests were carried out and the results achieved were satisfactory. The ANN type used was feed forward with 32 inputs, 16 neurons in the hidden layer and 8 neurons at the possible output layer. Sigmoid transfer function was used in the two last layers.

Figure 11 shows the network training results, for which it was used the algorithm TRAINGDX.

After the training the network validation was performed using now the second set of artificial cards with 100% correct results.

For the final test the 6101 real downhole dynamometer cards were used and the following result was achieved:

a) 11 card were not classified since the neurons at the output layer held values below the limit established by the criteria (0,1).

b) 69 cards were wrongly classified. However, from these 69 cards, 30 of them were cards pre-diagnosed as “plunger hitting top” when in fact they were “normal”

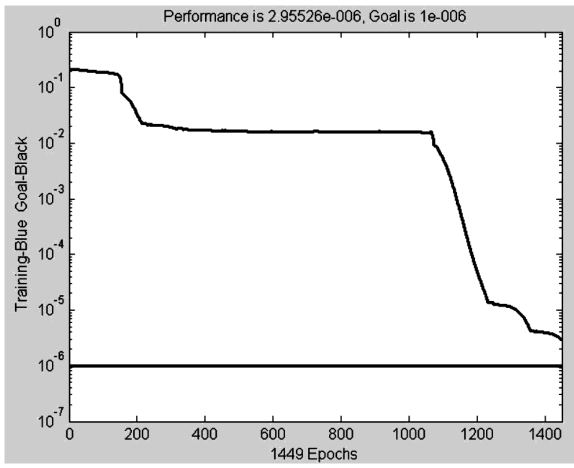


Figure 11. Training results from the ANN classifier.

When the above results were shown to a human expert, he observed that he would have considered as an acceptable diagnosis produced by the artificial neural network. That represents a considerable improvement in the results.

Summing it up, from the 6,101 cards which were tested, the total classification error was found to be 1,31%.

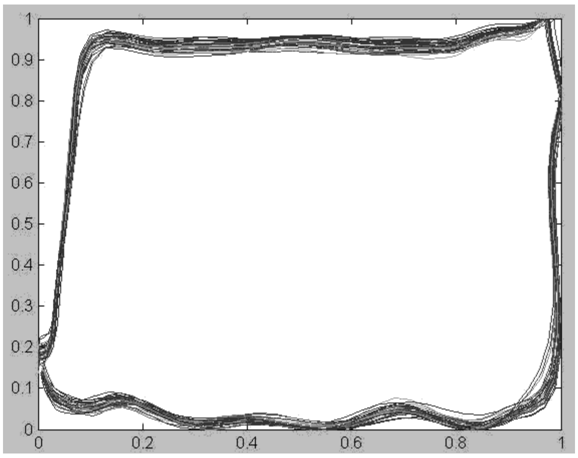


Figure 12. Error analysis in the classification.

5 CONCLUSIONS

The present work shows that the generation of artificial standards for training neural networks in order to analyze the pump mechanic system in oil elevation is feasible. The results shown here leave open the possibility of creating a scheme that not only incorporate the complete set of classes of anomalies, but which is also able to integrate the data base of real automation systems.

6 ACKNOWLEDGEMENTS

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