

# A procedure of fault detection for driving systems using self-organizing neural networks

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**Abstract**--In the paper it is proposed a neural network based procedure for the recognition of faults to a DC driving system. The analysis procedure of the faults can be used to warn the human user when a new class of faults is detected.

**Index Terms**--fault recognition, neural networks, pattern recognition, estimated domains.

## I. INTRODUCTION

In this paper we have been made a study on the recognition capabilities of faults which may appear in D.C. electrical driving systems. Generally, a diagnosis problem first supposes establishing faults that may appear during functioning of the electrical driving systems, and then the processing of data in order to extract the characteristics which emphasis the faults.

The paper presents the aspects regarding to the approach of the diagnosis problems which use an incomplete data set. The data set is considered incomplete when it doesn't offers a relevance of the occupied domains of the corresponding defect classes and/or it doesn't content vectors of some defect classes which are manifesting during operation.

In the implementation of the classifier we used self-organizing neural networks, because they offer a high flexibility in completing the data set of existing classes as well as of the classes which are not found in the initial data set.

The following aspects are presented:

1. forming the data set using parametrical identification techniques and the implementation of classifier using self-organizing neural networks;
2. completion of the data set and adding new defect classes to the initial data set.

## II. THE EXTRACTION OF THE CHARACTERISTICS AND THE DETERMINATION OF THE TRAINING SET

In order to extract the characteristics of the training set for recognizing the faults of the D.C. driving system, it must establish the relationships between the parameters resulted in the identification and the real system parameters, which

may alter during operation. Depending of the parameter modification and of the initial data set, the defect is assigned to one of the initial classes.

In the case study presented in the following sections the transfer function of the D.C. motor is given by the equation:

$$G_m(s) = \frac{\Omega(s)}{U(s)} = \frac{\Phi \cdot K_E}{J_m \cdot L_a \cdot s^2 + \left(\frac{F_a}{J_m} + \frac{R_a}{L_a}\right) \cdot s + \left(\frac{F_a \cdot R_a}{J_m \cdot R_a} + \frac{2 \cdot \pi \cdot \phi^2}{J_m \cdot R_a}\right)} \quad (1)$$

where:

- $U$  - the induced command voltage;
- $\Omega$  - the angular speed;
- $J_m$  - the inertial torque;
- $F_a, K_E$  - constants
- $R_a$  - induced resistance
- $L_a$  - induced inductance
- $\Phi$  - inducting flow

Among all the faults which may appear to a D.C. motor [7], a part of them is represented by those which produce the modification of the parameters  $R_a$  and  $\Phi$ . For example, the reduction of the contact surface of the collecting brushes and the diminishing of the slots of the ventilator, both produce variations of the parameters  $R_a$  or/and  $\Phi$ . At the beginning, we considered three situations: the normal operating situation, the situation with 10% variation of parameter  $R_a$  and the situation with -10% variation of  $\Phi$ . The situation with 10% variation of  $R_a$  and -10% variation of  $\Phi$  in the same time it will be investigated later in the paper, in order to complet the initial data set with a new class.

We determined the parameters which are modifying during functioning of the DC motor using the answer to the step signal of the transfer function described by equation (1). For the identification of the transfer function of the D.C. motor we used an optimization procedure of first order, as for example the Gauss-Newton method. This procedure is used because we obtain a realization, by a simple step signal, which permits the parameter identification to a high precision. It is well known that the parametrical optimization methods fail to an initial point value far from the optimum value. This problem is avoided as, in many

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situations, the values of the parameters corresponding to faults are not very far from the nominal values. In this context, the problem of the initial point is solved and the optimization procedure will determine the optimum value with a high precision.

In figure 1, it is illustrated the answer of the DC motor to a step signal, described by equation (1). It is considered the case when the answer is affected by an internal disturbance or by a measurement error which is manifesting to the output of the system.

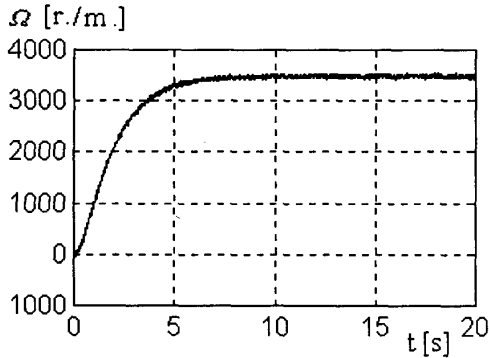


Figure 1. The answer of the DC motor to a step signal.

The characteristics of the classes which compose the data set are determined using the transfer function given by relation (2). This transfer function is obtained through a standard identification procedure, mentioned above, with data similar to those depicted in figure 1.

$$G(s) = \frac{\Omega(s)}{U(s)} = \frac{n}{s^2 + d_2 \cdot s + d_3} \quad (2)$$

Parameters  $R_a$  and  $\Phi$  are calculated with the following relations:

$$R_a = L_a \cdot \left( d_2 - \frac{F_a}{J_m} \right), \quad (3)$$

$$\Phi = \sqrt{d_3 - \frac{F_a \cdot R_a}{J_m \cdot R_a}} \cdot \frac{J_m \cdot R_a}{2 \cdot \pi} \quad (4)$$

The training set contains the following situations: normal operating (class 1), operating with 10 % deviation of resistance  $R_a$  (class 2), operating with -10% deviations of  $\Phi$  (class 3). These classes are illustrated in figure 2.

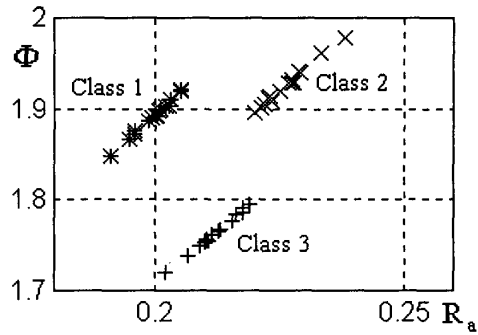


Figure 2. Class 1-normal operating, Class 2-operating with 10% deviation of  $R_a$ , Class 3 - operating with -10% deviation of  $\Phi$ .

### III. TRAINING THE NEURAL NETWORK

For the implementation of the classifier, we used a self-organizing neural network [2] with six prototype-vectors for each class. Consequently to the training of the neural network, the estimated domains corresponding to each class have been delimited. The distance between the marked dots and the closest prototype is less than 0.0015.

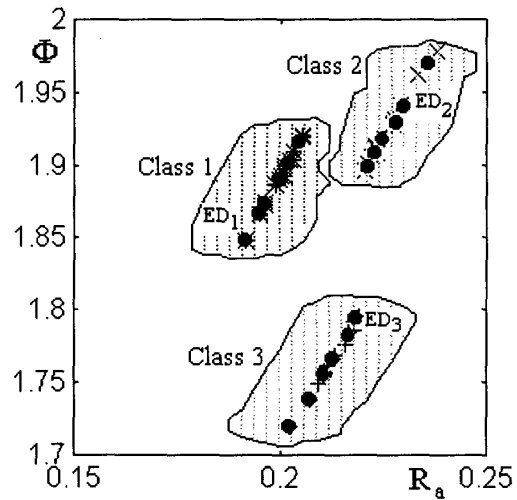


Figure 3: • - The prototype of the classes;  $ED_i$  - the estimated domains of class  $i$ .

One can see that using self-organizing neural networks, it has been obtained good performances of the classifier on the testing data set.

### IV THE COMPLETION OF TRAINING DATA SET

In many situations, during the classifier utilization, it is possibly to obtain patterns which do not belong to the classes of the initial data set [1]. Another possibility is the situation when a pattern belongs to a class, but it is

relatively distant from the patterns contained in the initial data set. We used two pre-defined parameters in order to complete the existing data set, both with patterns which will be attached to initial classes and with patterns which form a new class distinct of the classes contained in the training set

The first parameter is called *the selection threshold of a new pattern to an existing class*. If a pattern has all the distances to all other patterns of a class larger than this selection threshold, then the respective pattern will be attached to initial patterns.

The second parameter is called *the selection threshold of a pattern to a new class*. If a pattern which is presenting to the classifier has all the distances to all existing prototypes larger than this threshold, then the human expert is notified of the existence of a new class. The patterns of the new class are added to the existing data set on the basis of the selection threshold of a pattern to an existing class. The neural network is retrained with new data set. In figure 4 it is presented the case of a new class, formed when both  $R_a$  and  $\phi$  vary with 10% respectively with -10%.

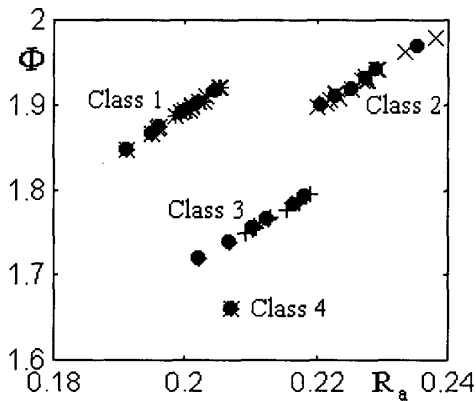


Figure 4. a) The moment of detection of a new class (Class 4)

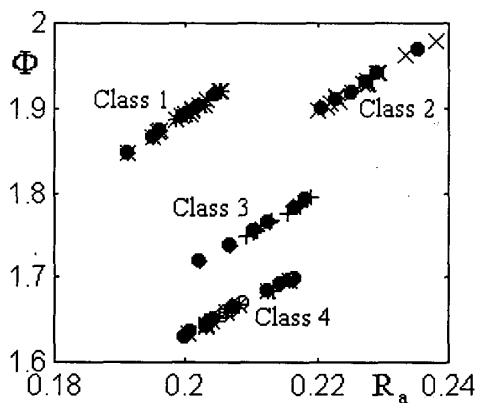


Figure 4. b) The completion of class 4 with new patterns

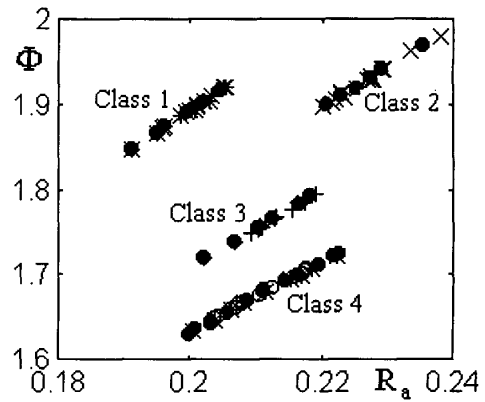


Figure 4. c) The end of completion of class 4

## V. CONCLUSION

Using the techniques of identification and recognition based on neural networks, it is possible to implement the classifiers with recognizing capabilities of the faults which may appear during functioning of a D.C. driving systems. This approach is based on the fact that any altering of a system parameter leads to the modification of the step answer and implicitly to the modification of the determined parameters in the identification.

An actualization procedure for the fault classes has been presented in the paper. This procedure can be used to warn the human user when a new class of faults is detected. We used self-organizing neural networks and the notion of selection threshold in order to decide if a fault belongs to an initial class or not

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