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FAULT DIAGNOSIS AND AUTOMATIC EXTRACTION OF FUZZY RULES IN AC MOTORS

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Abstract In this paper a new approach to fault diagnosis in an AC motor is introduced. This system combines a neuro-fuzzy system called FasArt (Fuzzy Adaptive System ART based) and the well-known *fuzzy k nearest neighbor algorithm.*
A set of 15 types of non destructive faults has been tested, reaching a high degree of early fault detection and fault type recognition. Moreover, taking into account the neuro-fuzzy nature of the FasArt model, a set of fuzzy rules, containing the knowledge learnt by the system, has been extracted. These rules permit a transfer of the knowledge from a numerical to a symbolic level where the fuzzy rules describe the fault in linguistic terms that can be interpreted by humans in an easier way.

Keywords: Neuro-fuzzy system, fuzzy rules, fault diagnosis, motor.

1. INTRODUCTION

For most real-world problems in modern industries there are a lot of data about the development of these processes. These data contain the knowledge about the behaviors that rule these processes and how these are ruled, but these aspects are hidden in data and are not directly accessible to humans. One of the most important aspects of any research work is to obtain the knowledge about the process and to be able to interpret and understand it.

Some approaches to extract the knowledge hidden in the data can be found in the bibliography: in (Wang and Mendel, 1992) and (Abe and Lan, 1995) fuzzy rules are generated from examples, in (Fu, 1994) a generation of rules from neural networks is described, etc. These methods permit the knowledge to be transferred from a numerical level to a symbolic level which is easier to humans.

Fuzzy logic and neural networks are two techniques that have been successfully applied to problems in several areas. These neuro-fuzzy systems combine the advantages of the two paradigms: learning from examples and capacity for dealing with fuzzy information. In this paper a neuro-fuzzy ART based system, FasArt, is used as the kernel of the system for detecting and classifying incipient faults as early time as possible, before the machine eventually suffers a failure or permanent damage. The knowledge learnt by the neuro-fuzzy system has been extracted as a fuzzy rule set containing the knowledge about the faults in “human” terms.

This system has been applied to an AC motor in order to carry out fault diagnosis. Several types of electrical motors are extensively used in a great variety of industrial environments. Safety, reliability, efficiency and performance are some of the most interesting aspects

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concerning motors. In order to reach high levels in these aspects, monitoring, on-line fault detection and automatic diagnosis are needed in modern industry. A review of the most usual motor problems, and the applied techniques are in (Finley and Burke, 1994), (Chow, 1997), (Benbouzid, 1999), (Nandi and Tolyat, n.d.) and (Arnanz *et al.*, 2000).

The proposed neuro-fuzzy system uses the FasArt model (Cano *et al.*, 2001) and, as auxiliary, the *fuzzy k nearest neighbor algorithm*. The FasArt model is a supervised system that has been applied successfully to several problems: pattern recognition (Sainz Palmero *et al.*, December 2000), system identification (Sainz Palmero *et al.*, 2001), etc. In this case, it is combined with the well known *fuzzy k nearest neighbor algorithm* and applied to the detection and classification of faults in an AC motor. The integration between the two components of this approach is carried out in the learning stage, the *k mean fuzzy* algorithm allows the input values of the learning data set to be labelled in an easier and more effective way than if this process is done by hand.

Moreover, after training the neuro-fuzzy system, the knowledge learnt by FasArt can be explained by a set of fuzzy rules that permits a better understanding of the knowledge involved in the process.

The paper is organized as follows: First, the neuro-fuzzy system FasArt (the kernel of the approach), is briefly described. Then the fuzzy k mean nearest neighbor algorithm and the way in which both are integrated are explained briefly. In addition a description of the experimental motor laboratory plant, the tests carried out, the results and the fuzzy rules obtained are described and discussed in sections 4.2 and 4.3. Finally, the main conclusions of work are set out.

2. FASART MODEL

FasArt (Fuzzy Adaptive System ART based) (Cano *et al.*, 2001) is a supervised neural network architecture based on the Adaptive Resonance Theory. In this model the neuron activation function employs a true fuzzy operation, associating each category to a fuzzy set, for which each input pattern produces a membership degree. Due to these changes, FasArt has several advantages over Fuzzy ARTMAP:

- It achieves a dual membership/activation function. A new activation function for each neuron k in F_2^a is defined (see Figure 2) as the product of fuzzy membership degrees on each input feature i.e.:

$$\eta_{R_k}(I) = \prod_{i=1}^{m} \eta_{ki}(I_i) \qquad (1)$$

where $I = (I_1, \ldots, I_m)$ is the input pattern and $\eta_{ki}(I_i)$ is the membership degree of input I_i to unit k in layer F_2^a, given by:

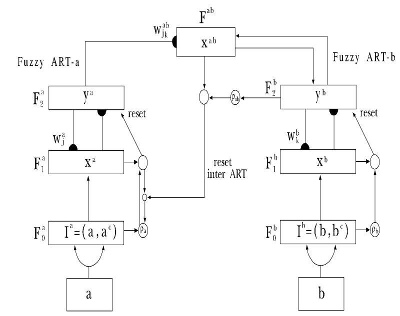

Figure 1. FasArt network architecture.

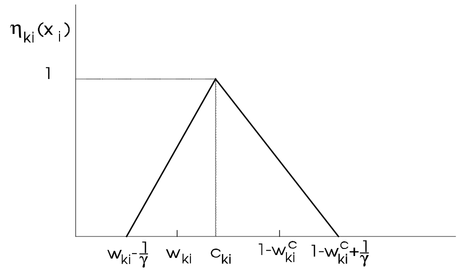

Figure 2. Membership function.

$$\eta_{ki}(I_i) = \begin{cases} \max\left\{0, \dfrac{\gamma(I_i - w_{ki}) + 1}{\gamma(c_{ki} - w_{ki}) + 1}\right\} & \text{if } I_i \le c_{ki} \\ \max\left\{0, \dfrac{\gamma(1 - I_i - w_{ki}^c) + 1}{\gamma(1 - c_{ki} - w_{ki}^c) + 1}\right\} & \text{if } I_i > c_{ki} \end{cases} \qquad (2)$$

where $W_k = (w_{k1}, w_{k1}^c, \ldots, w_{km}, w_{km}^c)$ and $C_k = (c_{k1}, \ldots, c_{km})$ are weight vectors associated to neuron k. Although triangular membership functions have been selected here (see Figure 1), gaussian or bell-shaped functions could also have been used. This duality of the weights allows each unit of F_2^a to be represented as a fuzzy set.

- The weight vector W_k has the same functionality as in Fuzzy ARTMAP, but a new weight vector, C_k, is defined for each neuron k of the F_2 levels, through a similar learning law as for W_k. C_k represents the central point of the triangular membership function, as shown in Figure 1.
- FasArt performance is affected by some user-tuned parameters inherited from Fuzzy ARTMAP: a vigilance parameter in each unsupervised module (ρ_a, ρ_b) controls the maximum allowed size of categories (in FasArt, the maximum support for fuzzy sets). During the test, ρ_a may be used to produce an *"unidentified"* answer if there is low confidence. Learning rates (β_a, β_b and β_a^c, β_b^c for the new weights vector C) determine how fast categories should include prototypes. Usually $\beta_a = \beta_b = 1$ (fast-learning).

In addition, the degree of fuzziness can be controlled through values of the parameter γ. Values of $\gamma \to \infty$ produce crisper fuzzy sets, while values of $\gamma \to 0$ increase the fuzzy nature of sets. This value determines the support of the fuzzy set.

- The relations stored in the inter-ART map, Figure 1(a), can be interpreted to construct a fuzzy rule set, with fuzzy sets in the input space defined by ART_a categories and in the output space by ART_b categories, obtaining rules of the following form:
  - IF I^a IS $R_j AND...$ THEN I^b IS R_k

  where I^a, I^b are linguistic variables and R_j, R_k are fuzzy sets in the input and output space respectively.
- The interpretation of FasArt as a fuzzy logic system permits the use of a defuzzification method in order to calculate a numeric output. In this case, the defuzzification method based on the average of fuzzy set centers is employed. Therefore, given an input pattern $I = (I_1, ..., I_n)$ presented in the test phase, the output is obtained by:

$$y_m(I) = \frac{\sum_{l=1}^{N^b} \sum_{k=1}^{N^a} c_{lm}^b w_{kl}^{ab} \eta_{R_k}(I)}{\sum_{l=1}^{N^b} \sum_{k=1}^{N^a} w_{kl}^{ab} \eta_{R_k}(I)} \qquad (3)$$

3. FUZZY K-NEAREST NEIGHBOR ALGORITHM

This is the fuzzy version of the *fuzzy k nearest neighbor* decision rule (Keller *et al.*, 1985) that has been applied to a lot of problems in several areas. The crisp nearest-neighbor classification rule assigns an input sample vector to the class of its nearest neighbor. On the another hand, the fuzzy k-nearest neighbor algorithm assigns class membership to a sample vector rather than assigning the vector to a particular class. In addition, these membership values provide a level of confidence about the resulting classification.

The basis of the algorithm is to assign membership as a function of the vector's distance from its k nearest neighbors and those neighbors' memberships in the possible classes.

FasArt is a supervised system, so the correct outputs to the inputs must be provided in the learning stage. In the case being dealt with here, each data set has several thousand data and several types of faults are considered and represented as overlapped clusters and trajectories, so each input must be labeled with membership values to each kind of fault. Using the fuzzy k nearest neighbor algorithm this task is done in an easier way than if the labels are provided by hand. But this is not a perfect method and it must be revised to avoid incorrect labellings, but there are not too many mistakes.

4. FAULT DIAGNOSIS OF AN AC MOTOR

The motor laboratory plant is composed of two Leroy-Somer induction motors LS132ST with three phases, 4 poles, 28 rotor bars and 36 stator slots with a power of 5.5 Kw each. The power supply frequency is 50 KHz and there is a delta connection. This motor plant has a sensor set to get a fine monitoring: the sensors include those for: voltage, current, temperature, magnetic flux, optical encoders, etc.

The experiments involved only non destructive faults due to the economic costs of the destructive tests. 15 different types of faults were tested:

- Normal functioning.
- Important unbalanced power supply in the three phases.
- Unbalanced power supply in the three phases.
- Resistor stator variation ($\triangle$) in the three phases.
- Unbalanced mechanical load.
- Fault in the angular speed encoder.
- Fault in voltage sensor in the three phases.

4.1 *Data acquisition and processing*

The data sets were acquired by a frequency of 25 MHz from the sensors in the motor plant. For each fault type 2-4 data sets were obtained, each containing 35000-40000 sample data of the variables that are used as inputs to the neuro-fuzzy system. These input variables are: 3 phase currents (I_1, I_2, I_3), 3 phase power (V_1, V_2, V_3) and angular speed (ω). One data set was employed in the learning stage and the other sets for testing each fault considered.

In order to improve the performance in the classification process, the electrical variables were processed using their effective values.

4.2 *Experimental results*

The experiments were carried out as follows: the fault was generated when the stationary functioning mode (normal mode) of the motor was reached. Then the motor returned to normal functioning when possible.

Using the data set generated, as explained in the previous sections, the neuro-fuzzy system is able to learn to classify or fault diagnosis at each point of a fault trajectory throughout its temporal evolution. In the test stage, the system provides a set of confidential diagnosis values to each of the fault types considered for each time point of the trajectory.

Analyzing the output generated by the FasArt module, this can detect the learnt faults at an early stage, when the fault is incipient, because in this situation the confidence output value of the normal functioning is not the best and/or there are some confidence values that have similar values to it. Also, a diagnosis time

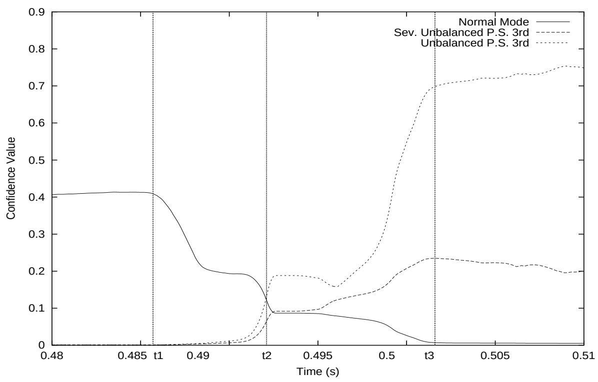

Figure 3. Evolution of FasArt confidence values throughout a fault evolution. (t_1), generation time, (t_2) detection time and (t_3) diagnosis time.

is generated when a new best confidence value is obtained and its value is bigger than the rest of the fault alternatives. These times can be observed in Figure 3 as well as the evolution of the functioning of the motor: normal mode until t_1, in this time the fault is generated and it is detected at t_2. Finally the type of fault is identified at t_3. Both times, t_1 and t_2, are considered on a soft or not too restricted criterion, so a hard time detection and diagnosis could be obtained by FasArt if necessary, using a more restricted criterion.

Three parameters have been chosen to evaluate the results:

- Detection time for each type of fault.
- Diagnosis time, which is obtained when a new best confidence value is obtained and its value is bigger than the rest of the fault alternatives.
- Successful rate of the diagnosis made by the system. This is the classification generated by the system for each time value of the input variables throughout the fault evolution.

The results obtained in the experiments are described bellow:

- Important Unbalanced Power Supply 1^{st}: 0.0013, 0.0232, 100%.
- Important Unbalanced Power Supply 2^{nd}: 0.0013, 0.0188, 100%.
- Important Unbalanced Power Supply 3^{rd}: 0.0008, 0.0179, 100%.
- Unbalanced Power Supply 1^{st}: 0.0013, 0.0202, 15%.
- Unbalanced Power Supply 2^{nd}: 0.004, 0.0151, 77%.
- Unbalanced Power Supply 3^{rd}: 0.0052, 0.0159, 100%.
- Voltmeter 1^{st}: 0.0033, 0.0077, 100 %.
- Voltmeter 2^{nd}: 0.0059, 0.0084, 100%.
- Voltmeter 3^{rd}: 0.0073, 0.0089, 100%.
- $\triangle$ Stator Resistor 1^{st}: 0.0094, 0.0116, 34%.
- $\triangle$ Stator Resistor 2^{nd}: 0.0075, 0.0103, 100%.
- $\triangle$ Stator Resistor 3^{rd}: 0.0082, 0.011, 100%.
- Encoder: -,-, 0%.
- Unbalanced Mechanical Load: -, -. 0%.

Observing these results, there are only two kinds of fault that are not detected: encode failure and unbalanced mechanical load. In this case, it is not possible to detect by using the real input variables them because they are confused with normal functioning mode, i.e., both cluster types are mixed (see Figure 4).

The rest of the faults have early detection and diagnosis times. When the fault is classified the rate of success is 100%, but "Several Unbalanced Power Supply 2^{nd}" has a 77% success rate and other two faults have lower rates: "Unbalanced Power Supply in the 1^{st}", the fault is confused with "Stator Resistor in the 1^{st} phase" and "Important Unbalanced Power Supply in the 1^{st} phase". The second is the "Stator Resistor Variation in the 1^{st} phase" that has a rate of about 34% and is confused with the "Normal functioning". Even so in these cases in which that the system does not work as well as the rest of the faults, the diagnosis uncertainty is limited to two possible fault alternatives.

4.3 *Fuzzy rules*

Moreover, the knowledge stored by the fuzzy-neuro nature of the system can be expressed by fuzzy rules. The set of rules obtained can be summarized in Table 1, which shows that the normal functioning mode can be explained by using only three fuzzy rules, and similarly with the rest of the modes or faults. One of the most significant aspects is the that rules number for a fault type is different depending of the electrical phase treated. It could be forced by the electrical unbalancing of the plant and the constructive aspects of the motor.

Table 1. Fuzzy database.

Type of failure	N^o of Fuzzy rules (in each phase)
Normal	3
Important Unbalanced Power Supply	5 (1^{st}) 7(2^{nd}) 6(3^{rd})
Unbalanced Power Supply	3(1^{st}) 5(2^{nd}) 3(3^{rd})
$\triangle$ Stator Resistor	3(1^{st}) 4(2^{nd}) 5(3^{rd})
Unbalanced Mechanical Load	1
Encoder Failure	1
Voltmeter Failure	2(1^{st}) 3(2^{nd}) 3(3^{rd})

In Figures 4, 5, 6, 7 and 8 some of the fuzzy rules representing the knowledge learnt by the fuzzy system can be observed. The antecedent of the fuzzy rule is one of the fuzzy prototype/neuron of F_2^a defined by a set of fuzzy sets, each one for each input signal, and similarly, the consequence is a Fuzzy prototype/neuron in F_2^b defined by a set of fuzzy sets, one for each type of fault considered. In this way the fuzzy rule in Figure 4 can be interpreted as "Normal functioning" mainly and, as it has been commented previously, this mode hides the faults in the "Encoder"

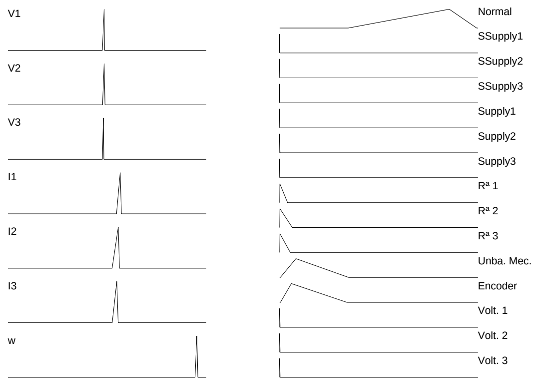

Figure 4. Fuzzy rule for normal functioning.

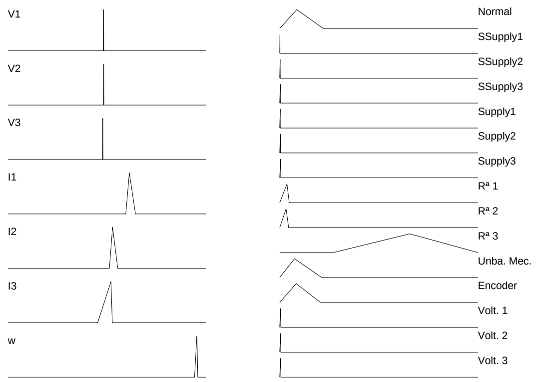

Figure 5. Fuzzy rule for fault in $\triangle$ Stator Resistor in the 3^{rd} phase.

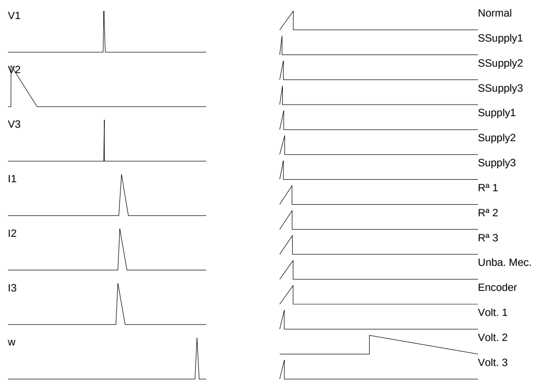

Figure 6. Fuzzy rule for fault in Voltmeter in the 2^{nd} phase.

and the “Unbalanced mechanical load”. In Figure 5 the rule is representative of a fault in the “Stator Resistor in the 3^{rd} phase” because, when the defuzzification process in this rule is carried out for each fault type, the confidence values obtained by the other fault alternatives are smaller than in the “Stator resistor” case. Similarly, in Figures 6 and 7, the fuzzy rules describe faults in the “Voltmeter on the 2^{nd} phase” and “Voltmeter on the 3^{rd} phase” respectively. A rule about “Important Unbalanced Power Supply” and “Important Unbalanced Power Supply” can be seen in Figure 8.

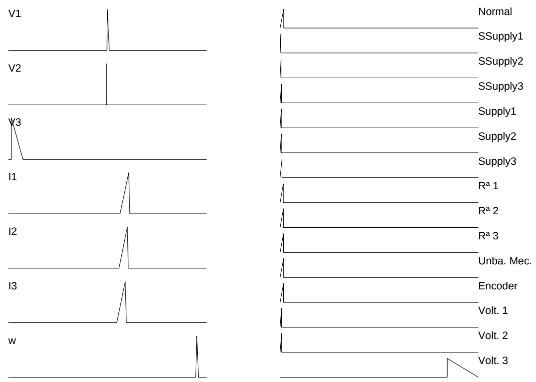

Figure 7. Fuzzy rule for fault in Voltmeter in the 3^{th} phase.

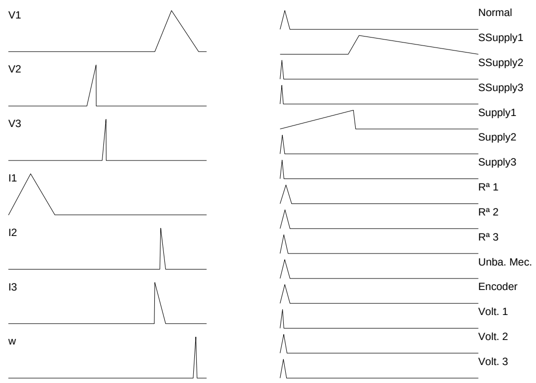

Figure 8. Fuzzy rule for fault in Important and Soft Unbalanced Power Supply 1^{st} phase.

5. CONCLUSIONS

The neuro-fuzzy based on the ART theory, FasArt, has been used to carry out two tasks:

- Fault detection and diagnosis of an AC motor.
- Extraction of the knowledge by fuzzy rules.

The use of the fuzzy k nearest neighbor algorithm in the learning stage of the fuzzy system has achieved a labelling of overlapped fault data. In this way the system is able to work with the faults at any point of their trajectories or time evolution.

The results obtained by FasArt model, through its confidence values for each fault type, have enabled the majority of the considered fault types to be detected and a fault diagnosis to be made. The success rate of classification/diagnosis (about 77% – 100%) and the detection and diagnosis times (about $10^{-4} - 10^{-3}$ *seconds*) provided by this approach for 15 types of faults, enable actions to be taken to avoid failures or permanent damage to the motor. Only two types of fault are not detected or classified, but in the cases in which the system does not work well (about 15% – 34%), the possible fault alternatives are reduced to two or three types of the set considered.

Finally, a reduced set of fuzzy rules is extracted from the neuro-fuzzy system. In this way, the knowledge learnt and stored in the system can be expressed in linguistics terms and a better understanding of the process can be achieved and used in other systems or tasks.

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