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Interval Type-2 Fuzzy Classifier for Minimization of the Faults Identification Error

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Abstract: The faults diagnosis and detection in real systems is a hard task, mainly due the occurrence of false alarms in the monitoring system teasing unplanned downtime and stoppages in production. To avoid these undesired behaviors some strategies are used to become the monitoring more robust the external interference, with this purpose, in this paper is used an interval type-2 fuzzy system. An interval type-2 fuzzy system, do not presented membership function unique or limited, but an uncertainty region, this shaded region known as footprint of uncertainty (FOU), allows considered uncertainties and nonlinearity typical of noisy real systems and frequently associated to the measurement equipments which cause identification errors and consequently can compromise the good function of the monitoring systems, for instance. For the test of the proposed tool will be used parameters of an Auto Regressive eXogenous (ARX) models, and a comparison with classical fuzzy systems is done for quantify and qualify the results.

Keywords: interval type-2 fuzzy system, uncertainties analysis, faults identification techniques

NOMENCLATURE

$y(k)$ = *output signal*
$u(k)$ = *input signal*
$v(k)$ = model error
q^{-1} = discrete delay operator
q^{-d} = transport delay operator

a_1 = denominator parameters of the model in time-discrete
b_1 = numerator parameters of the model in time-discrete
$K(t+1)$ = estimated gain
$P(t+1)$ = covariance array

Greek Symbols

$\hat{\theta}$ = vector of estimated parameter
ε = prediction error
μ = membership function

INTRODUCTION

Fault detection is a hard task principally when they are small (incipient faults) or hidden. Incipient faults (driftwise) enhance over time and it can lead the system working outside operating point, and therefore in failure or malfunction, when none preventive measure is taken. In this paper will be studied faults diagnosis techniques applied in induction motors subjected the incipient fault. These malfunctions need to be detected and isolated before system normal operating is jeopardized. (Chow, 1997, Isermann, 2006, & Patton, 2000).

Although induction motors are usually well constructed and robust, the possibility of incipient faults is inherent, principally due the operation condition that, frequently, these systems are submitted. Incipient faults are characterized by small deviations from normal behavior, whose the symptoms generally are camouflaged by control system, becoming difficult to observe them using detection classical methods as analysis of the temperature variations, vibrations or noises from system (Blanke et al., 2006 & Chow, 1997).

In this paper will be analyzed the behavior of an induction motor subject the incipient fault of type field winding turns partial short-circuit. With this purpose, a ramp signal with negative slope will be applied in the magnetizing reactance of the induction motor simulator described in Ong 1998, emulating the fault applied.

IDENTIFICATION TECHNIQUES

In the identification process is desired to get a mathematical representation of the plant, process, and fault. In this section it is used to represent the fault, technique based on process model, where the fault is detected through of the parameters of the first-order function in time discrete obtained by recursive least squares (RLS) estimator.

Process model

The fault detection based in process model consists in to detect malfunction and deviations of the normal behavior, by comparison of actual model with a set of mathematics model that represent the healthy system. Thus with relation the Fig. 1, a mathematical model of first order in the ARX structure should be obtained, whose parameters will be estimated by RLS, allowing thus detect the fault.

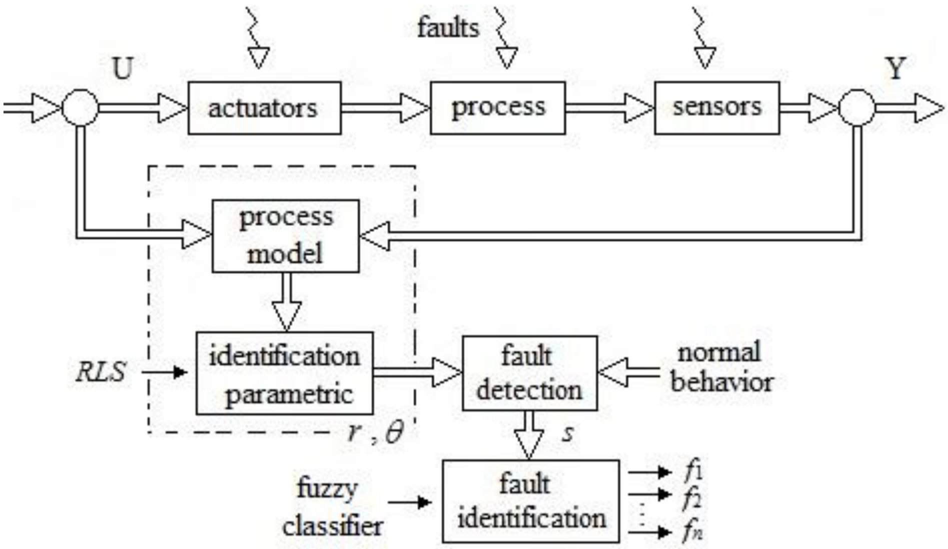

Figure 1 – General scheme of process model-based fault detection – based in Isermann, 2006

Identification system

The ARX model structure considered in the system linear identification process is given in (1) (Aguirre, 2007 & Isermann, 2006):

$$A(q)y(k) = q^{-d}B(q)u(k) + v(k) \tag{1}$$

where,

$$\begin{aligned} A(q) &= 1 + a_1 q^{-1} + \ldots a_{ny} q^{-ny} \\ B(q) &= b_1 q^{-1} + b_2 q^{-2} + \ldots b_{nu} q^{-nu} \end{aligned} \tag{2}$$

For a first-order system in the ARX structure considering disturbances nulls, the equation (1) becomes:

$$\frac{y(k)}{u(k)} = \frac{b_1 q^{-1}}{1 + a_1 q^{-1}} q^{-d} \tag{3}$$

and the parameters a_1 and b_1, of the model in time-discrete, are obtained using RLS technique.

Recursive least square technique with forgetting for parametric estimation

The algorithm of the recursive estimator, according Coelho & Coelho (2004), is an algorithm with several purposes such as, supervision, parameters tracking for adaptive control (self-tuning control), detection and diagnosis. Then, the uses of RLS allows, through measuring input and output variables of the process, obtain mathematical models in real time, which permit the preventive monitoring of the system, and the fault detection, when system shows deviations from normal behavior.

Following the mathematical development given in Coelho and Coelho (2004, p.114), the final form of the vector of recursively estimated parameters of the ARX model of first order in discrete-time at the instant (t+1) is as in (4):

$$\hat{\theta}(t+1) = \hat{\theta}(t) + K(t+1)\left\{y(t+1) - \varphi^T(t+1)\hat{\theta}(t)\right\} \tag{4}$$

where

$$K(t+1) = P(t+1)\varphi(t+1) = \frac{P(t)\varphi(t+1)}{1 + \varphi^T(t+1)P(t)\varphi(t+1)}$$

$y(t+1) - \varphi^T(t+1)\hat{\theta}(t)$ is conventionally utilized as definition of the variable error $\varepsilon(t+1)$.

Thus a vector of parameters is updated in real time and, by mean of parameters, which function as system status indicators, it is possible to detect faults.

TYPE-2 FUZZY SET

Introduced by Zadeh in (1975) as an extension of the concept of type-1 fuzzy set, type-2 fuzzy sets are three-dimensional, formed by a primary fuzzy set and a secondary fuzzy set, and therefore, type-2 fuzzy sets have grades of membership that are themselves fuzzy (Dubois, 1980) and (Liang & Mendel, 2000).

Definition of type-2 fuzzy set

A type-2 fuzzy set (Ã) is characterized by a membership function (MF) of the type-2 $\mu_{\tilde{A}}(x,u)$, where $x \in X$ and $u \in J_x \subseteq [0,1]$, so:

$$\tilde{A} = \{((x,u), \mu_{\tilde{A}}(x,u)) \mid \forall x \in X, \forall u \in J_x \subseteq [0,1]\} \tag{5}$$

where, J_x corresponds to the primary fuzzy set, defined in $0 \leq \mu_{\tilde{A}}(x,u) \leq 1$. For an ordinary fuzzy set (type-1 fuzzy set), where the uncertainties are eliminated, u becomes $\mu_A(x)$, and $0 \leq \mu_A(x) \leq 1$.

Primary fuzzy set

The primary fuzzy set is the set formed by all the primary membership functions (MFs) J_x.

$$FOU(\tilde{A}) = \bigcup_{x \in X} J_x \tag{6}$$

This region known as footprint of uncertainty (FOU), it is limited by lower MF and upper MF, as represented in the Fig. 2. The primary membership of x, which is denoted by J_x, is the dominion of the secondary fuzzy set, as represented in the Fig. 3. And the primary MF can be anyone of the type-1 MFs inside the FOU (Contreras, 2007).

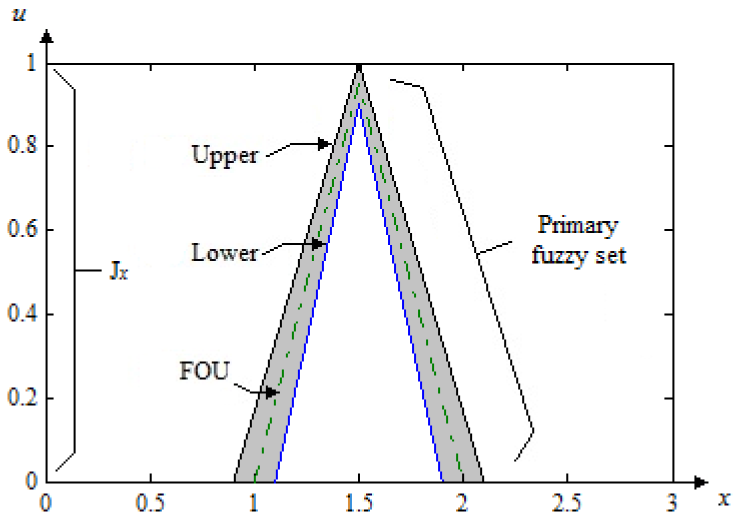

Figure 2 – Type-2 MF

Secondary fuzzy set

The uncertainties associated to the primary fuzzy set added to the secondary MF of the secondary fuzzy set, ensures the three-dimensional features of the type-2 fuzzy set, Fig. 3.

And knowing which the secondary MF, $\mu_{\tilde{A}}(x',u)$, define for $x' \in X$ and for $u \in J_{x'} \subseteq [0,1]$, thus the secondary MF is defined as in (7):

$$\mu_{\tilde{A}}(x = x', u) \equiv \mu_{\tilde{A}}(x') = \int_{u \in Jx'} f_{x'}(u)/u \tag{7}$$

where $f_{x'}(u)$ is the secondary degree of the secondary MF with membership between $0 < f_{x'}(u) < 1$. For interval type-2 fuzzy set $f_{x'}(u) = 1$. These tests will be considered interval type-2 fuzzy systems.

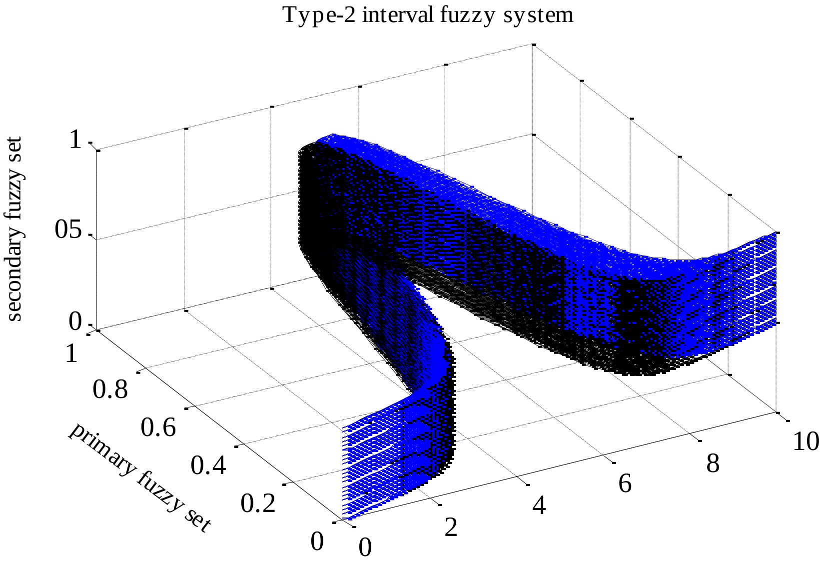

Figure 3– Three-dimensional membership function

Structure of a type-2 fuzzy system

As well as in ordinary fuzzy system, type-2 fuzzy system are formed by fuzzifier, rule base, inference engine, and output processor, in type-2 fuzzy system, the output processor includes, type-reducer and deffuzzifier as in the Fig. 3 (Liang & Mendel, 2000).

Fuzzifier

The inputs of the fuzzifier are generally accurate, non-fuzzy, i.e. crisp numbers, and in great part of the practical applications is common the use of fuzzifier of the type singleton, in the case of type-2 fuzzy system, is used type-2 singleton fuzzifier, although in Mouzouris and Mendel in (1997) for the case of noisy data is most adequate the use of nonsingleton fuzzifier, to which treats each measurement as fuzzy number.

Rule base

As in ordinary fuzzy system, in type-2 fuzzy system, the rule base is formed generically by input and output sets whose its antecedent and consequent are now of the type-2, and related by rules of type (IF… THEN…). In general, for type-2 fuzzy system the computational effort is bigger due the more quantity of rules to define rule base, rules to the upper boundary and lower boundary. Hence in order to overcome this problem, without loss of efficient of the technique, it was decided to use interval type-2 fuzzy set, where is admitted unitary the membership of the secondary MF, thus, the uncertainties handled will just be of the primary fuzzy set, related the FOU.

Inference engine in type-2 fuzzy system

In this stage the rules are combined and type-2 fuzzy set are generated in the output, from input type-2 fuzzy set, through of the use of meet and join operation. As explained previously, the use of interval type-2 fuzzy set simplified also the meet and join operation, and one of the problems which is to the choose of membership shape is resolved.

Given the activated interval set, $F^l(x')$, a type-1 fuzzy set as in (8),

$$F^l(x') = \left[\underline{f}^l(x'), \overline{f}^l(x') \right] \equiv \left[\underline{f}^l, \overline{f}^l \right] \tag{8}$$

$\underline{f}^l$ and $\overline{f}^l$ are the left bound point and right bound point of $F^l(x')$, known as firing strength. The operation meet happening individually between lower membership degree of the lower MFs $\underline{\mu}_{\tilde{F}_p^l}(x'_p)$, and between upper membership degree of the upper MFs $\overline{\mu}_{\tilde{F}_p^l}(x'_p)$, of the antecedent set F_1, as observed in (9) and (10).

$$\underline{f}^l(x') = \underline{\mu}_{\tilde{F}_1^l}(x'_1) \prod \ldots \prod \underline{\mu}_{\tilde{F}_p^l}(x'_p) \tag{9}$$

$$\overline{f}^{\,l}(x') = \overline{\mu}_{\tilde{F}_1^l}(x_1')\prod \cdots \prod \overline{\mu}_{\tilde{F}_p^l}(x_p') \tag{10}$$

The intersection operation, meet, relate the membership degree as in the Fig. 4. For this, in this paper is used the product as t-norm.

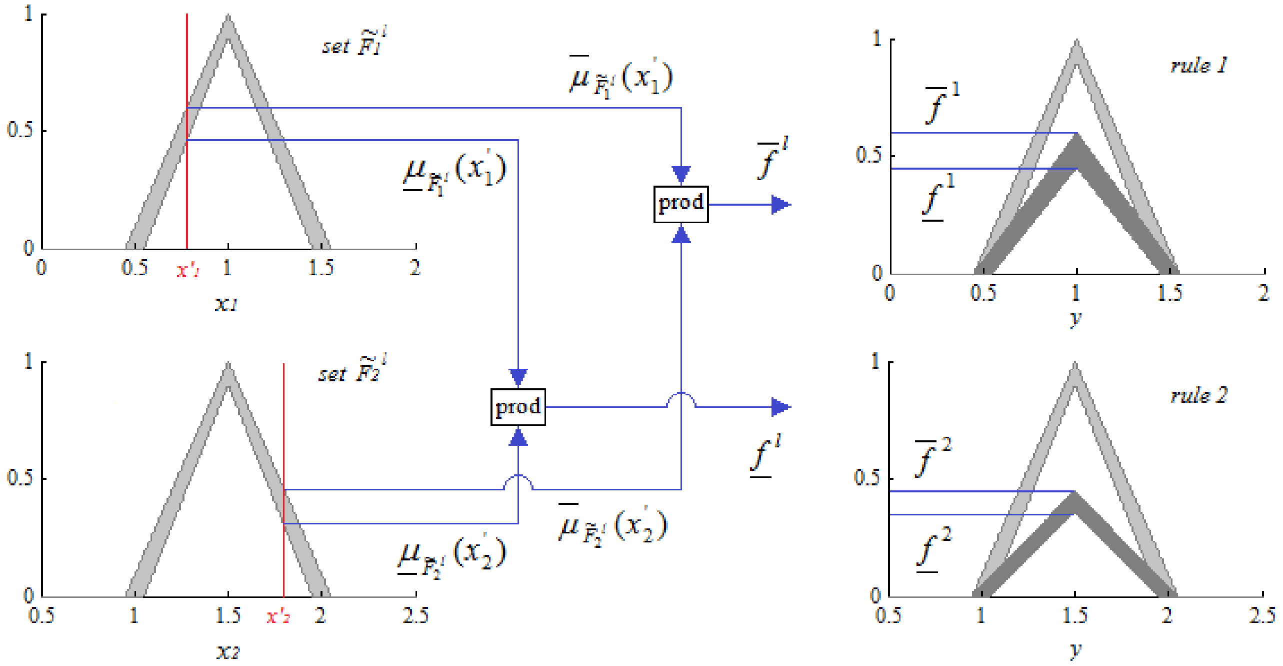

Figure 4 – Process description between input-antecedent, and antecedent-consequent of a type-2 interval fuzzy system of the type Mamdani with singleton input using the product as t-norm

The results of the consequents are obtained using the product as t-norm of the antecedents; the generated fuzzy set obtained by meet and join operations, and denoted by $\mu_{\tilde{B}}(y)$, it is showed in the shaded darker region of the Fig. 5.

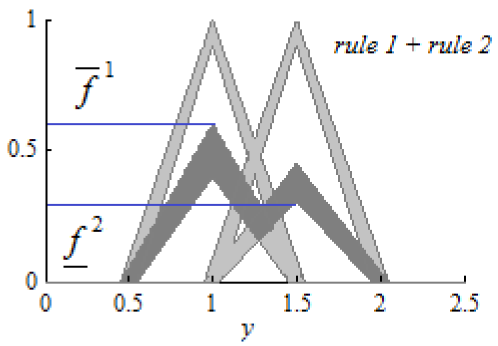

Figure 5 – Output set obtained by operation of interaction of the activated sets.

Type-reducer and defuzzifier

The type-reducer and defuzzifier makes parts of the output processor. The type-reducer is applied in a FOU of $\mu_{\tilde{B}}(y)$, which transforms the type-2 fuzzy set in an ordinary fuzzy set, and finally the defuzzifier, the fuzzy set in a crisp value. In an interval type-2 fuzzy system with singleton input, it is used a type-reducer of the type centroid (gravity center), whose reduced set is the interval between $Y_{T-R} = [y_l, y_r]$.

$$y_l = \frac{\sum_{i=1}^{M} f_l^{\,i} y_l^i}{\sum_{i=1}^{M} f_l^{\,i}}, \quad y_r = \frac{\sum_{i=1}^{M} f_r^{\,i} y_r^i}{\sum_{i=1}^{M} f_r^{\,i}} \tag{11}$$

And the crisp value is obtained by the arithmetic mean of the limits.

EXPERIMENTAL RESULTS

Initially the parameters of the function in discrete time were obtained by RLS technique. It were considered three operation points, one for each short-circuit level in coils stator, the Fig 6 showed the estimated parameters.

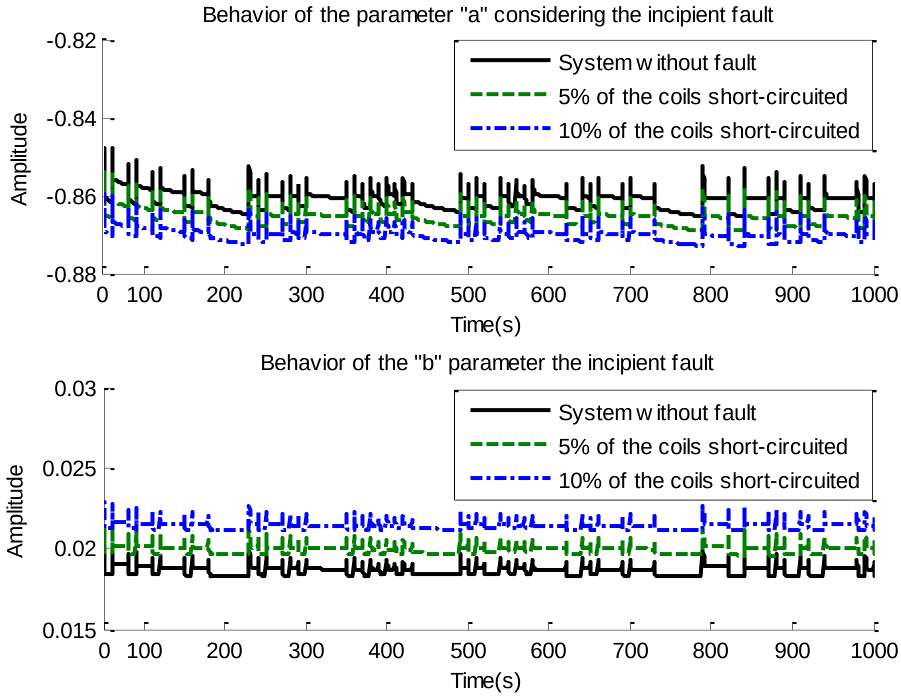

Figure 6 – Parameters of the discrete-time function obtained by RLS

And the Tab. 1, below, presented the mean of the estimated parameters, which will be base to build the membership function of the fuzzy systems.

Table 1 – Parameters of the model in time-discrete

Fault conditions	*a*	*b*
0%	0.8619	0.0186
5%	0.8663	0.0199
10%	0.8707	0.0213

Using type-1 fuzzy system

Initially to the development of technique will be considered triangular MFs, this choice ensures null error to value of center of the MFs. For type-1 fuzzy system are considered the dashed line of the Fig. 7, and for type-2 fuzzy system, the uncertainties associated the dashed line.

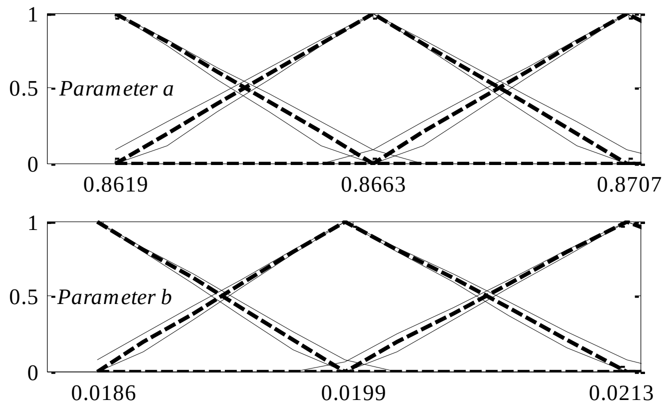

Figure 7 – Output set obtained by operation of interaction of the activated sets.

Type-1 fuzzy system

To identify the damaged degree in the system induction motor, it should be obtained the membership function for the center values (0%, 5%, and 10%), and the intermediary cases will be obtained for inference using the fuzzy classifier.

Considering 7% of the coils in short-circuit, this corresponds to x_{ta}=0.8681 and x_{tb}=0.0204, and the membership degrees are:

$\mu_{x2a} = -0.596$, $\mu_{x3a} = 0.4034$ → *membership degrees to parameter a*

$\mu_{x2b} = -0.617$, $\mu_{x3b} = 0.3830$ → *membership degrees to parameter b*

Where $\mu_{x2(a,b)}$ and $\mu_{x3(a,b)}$ represents the membership degrees of the *a* and *b* parameters.

Using the product as t-norm $\left(\mu_{x2(a,b)} \times \mu_{x3(a,b)}\right)$ is obtained an uncertainty region, which is input of a defuzzifier of the type centroid. Thus, the crisp value of the uncertainty region of the fuzzy set with centers in 5 and 10 is:

$$y_{def}(\%) = \frac{\mu_{x2a} \times \mu_{x3a} \times 5(\%) + \mu_{x2b} \times \mu_{x3b} \times 10(\%)}{\mu_{x2a} \times \mu_{x3a} + \mu_{x2b} \times \mu_{x3b}} = 6.47\%$$

Which the error is given as:

$$error(\%) = 100(\%) - \frac{6.47(\%) \times 100(\%)}{7(\%)} = 7.57\%$$

Resulting 6.47% of coils in short-circuit identified, what corresponds in an error of 7.57%. Now the same procedure will be made using interval type-2 fuzzy system.

Using type-2 fuzzy system

Considering the uncertainties in the MF's of the Fig. 6, and using the development of the eq. (8)-(10), it is obtained:

$$\underline{f}_2(x) = 0.3680$$

$$\overline{f}_2(x) = 0.4094$$

$$\underline{f}_3(x) = 0.1545$$

$$\overline{f}_3(x) = 0.1924$$

And applying the reduce-type centroid eq. (11), the lower and upper bounds obtained are:

$y_r = 7.0985$ → Upper bound

$y_l = 5.9784$ → Lower bound

The last stage happen in the defuzzifier, the crisp value is obtained by a simple arithmetic mean of the limits values above. Then the crisp value is:

$$y_{def}(\%) = \frac{y_r + y_l}{2} = \frac{7.0985 + 5.9784}{2} = 6.5384\%$$

Which the error is given as:

$$error(\%) = 100(\%) - \frac{6.5384(\%) \times 100(\%)}{7(\%)} = 6.594\%$$

This result show a value identified of coils in short-circuit closer of the real value which is 7%. Thus the interval type-2 fuzzy system gave an error of 6.594%, what does it mean a reduction in the identification error near the half, which justified the use of the proposal technique. The advantages of the proposal technique were observed for the other values of coils in short-circuit, as showed in the Tab. 2.

Table 2 – Percentage of coils in short-circuited identified considering incipient fault test, i.e. until 5% of coils in short-circuit)

Real Fault	Identified by Type-1 Fuzzy System	Identified by Type-2 Fuzzy System
0%	0.0000%	0.0000%
1%	0.2769%	0.3591%
2%	1.4721%	1.5400%
3%	3.3945%	3.3236%
4%	4.6884%	4.5970%
5%	5.0000%	5.0000%
7%	6.4786%	6.5384%

In the Tab.2, others levels of faults were presented, as well as percentage corresponding of coils identified by methods studied here. It was observed that interval type-2 fuzzy system minimize the identification error, i.e. it presented a value closer to real value of coils short-circuited. The Fig. 8 depicts quantitatively the advantages of interval type-2 fuzzy system with relation the ordinary fuzzy system, using for this the mean square error (MSE), which is the objective function to be minimized.

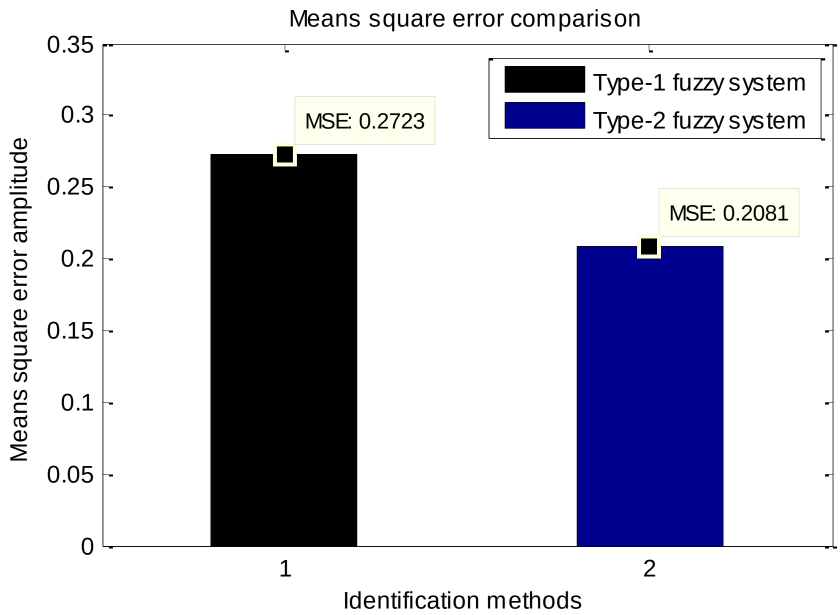

Figure 8 – Mean square error for the proposed methods

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