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An Interval Type-2 Fuzzy Logic Approach for Instrument Fault Detection and Diagnosis

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Abstract—**This paper presents an application of a Type-2 Fuzzy Inference System for fault detection and diagnosis (FDD) in an alternative gas compressor (Sales Gas Compressor - SGC) of a Gas Processing Unit (GPU). The SGC system operates at high loads compressing about 2.5 million cubic meters of natural gas per day. Due to this its operation conditions comprises high temperatures that can trip the system and shutdown the whole unit. In order to avoid such events a FDD system is needed. FDD systems reduce downtime, improve security operation and can contribute to reduce operational costs. Furthermore, early fault detection can extend the process life cycle preventing product deterioration as well as material and human damage.**

Index Terms—**fault detection and diagnosis, fuzzy c-means, instrumentation, interval type-2 fuzzy logic**

I. Introduction

In the last three decades process control and automation area had a tremendous improvement due to advances on computational tools. Many of regulatory control actions that were performed by human operators are now performed automatically with aid of computers. Nonetheless, in a process with hundreds of variables, instruments and actuators it is impossible that a person or a group can manage every and any alarm triggered by an abnormal event. Therefore the Fault Detection and Diagnosis (FDD) field had received extensive attention. According to [1], the current challenge for control engineers is the automation of Abnormal Event Management (AEM) using intelligent control systems. Inside this field, Instrument Fault Detection and Diagnosis is a potential tool to prevent process performance degradation, false alarms, missing actions, process shutdown and even safety problems. A well-known strategy related to this problem is preventive maintenance. In that, periodical tests and calibration are made in instruments. This is a cumbersome task where instruments are dismantled, cleaned, reassembled and calibrated. Even so, this is not a guarantee that faults will not occur [2]. This paper presents an Interval Type-2 Fuzzy Logic (IT2FL) classifier to detect and diagnose temperature sensor faults in an alternative compressor, named Sales Gas Compressor (SGC), operating in a Gas Processing Unit (GPU).

II. Instrument Fault Detection And Diagnosis - IFDD

Fault Detection and Diagnosis is concerned with detecting an abnormal event and finding its localization. FDD techniques use two basic approaches based on *a priori* knowledge about the process: model-based and process history-based. The former, also known as analytical redundancy, generates residuals between the process and its model in order to detect changes in parameters or variables of the process. In the latter a large amount of historic process data is required to extract features about the process that will be used in the diagnostic system. This feature extraction consists of a data transformation. Two transformation approaches can be adopted, namely, quantitative and qualitative [1], [3]. In the quantitative case, the feature extraction comprises the use of statistical methods such as Principal Component Analysis (PCA) or non-statistical methods based on Artificial Neural Networks (ANN) and Fuzzy Logic (FL). Most of the IFDD techniques use model-based techniques (analytical redundancy) due to the high costs required to implement hardware redundancy which needs at least three sensors to isolate a fault. In cases in which data measurement is noisy and incomplete or analytical model is not available, artificial intelligence techniques are good alternatives [2], [4], [5]. The recent popularity of process history-based methods is related to the complexity of industrial plants and the difficulty to model them, which also justifies the application of such a method to detect and diagnose faults in this work.

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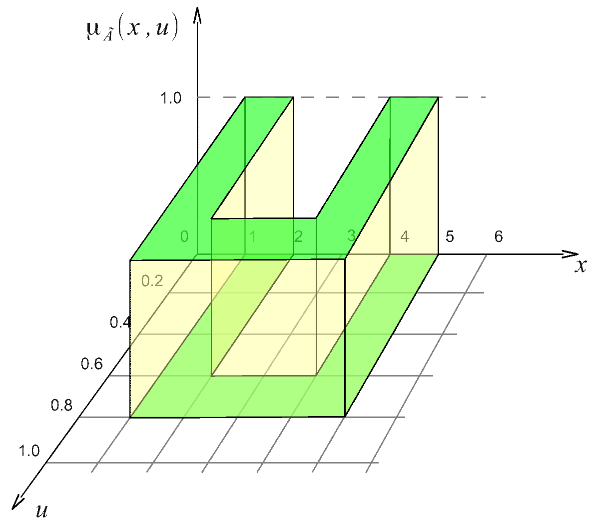

Fig. 1. Type-2 fuzzy set.

III. Fuzzy Logic

In [6] Zadeh introduced the concept of Type-2 Fuzzy Sets (T2FS) generalizing his former concept of ordinary fuzzy sets - Type-1 Fuzzy Sets (T1FS). In a T1FS membership functions are crisp and not capable of handling uncertainties. Otherwise in a T2FS membership functions are themselves fuzzy with each primary membership grade having a secondary grade [7] (Fig. 1).

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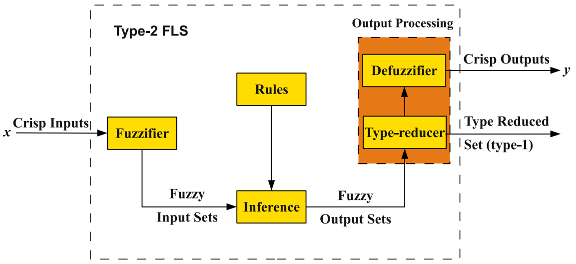

Fig. 2. Interval type-2 fuzzy logic system.

According to [8] this generalization enables modeling and minimizing the effect of uncertainties present in rule-based fuzzy inference systems. Although, a simplification is required in order to reduce the computational complexity of the general type-2 fuzzy sets operations. This simplification is achieved using interval type-2 fuzzy sets represented by an upper and a lower membership function defining the Footprint of Uncertainty (FOU). These are just simple T1FS and are "very useful when we have no other *a priori* knowledge about membership function uncertainties" [9].

An Interval Type-2 Fuzzy Logic System (IT2FLS) has five subsystems; fuzzifier, fuzzy inference system (FIS), rule-base, type-reducer and defuzzifier (Fig. 2).

The FIS subsystem uses many rules with some of them extracted from data and others from surveys applied to experts. To extract rules from data, [9] used a supervised clustering technique employing statistics to determine the mean and the standard deviation for each pattern. Another way to extract rules is using unsupervised clustering. A well-known technique used in unsupervised clustering is the Fuzzy C-means (FCM) [10]. The FCM algorithm comprises the minimization of the following cost function:

$$J = \sum_{k=1}^{n} \sum_{i=1}^{c} \mu_{ik}^{m} \|x_k - v_i\|^2 \tag{1}$$

Where n is the number of data points, c is the number of clusters, x_k is the k-th data point, v_i is the i-th cluster center, μ_{ik} is the degree of membership of k-th data in the i-th cluster and m is a constant that express cluster fuzziness, also called fuzziness exponent [11]. The degree of membership μ_{ik} is defined as

$$\mu_{ik} = \frac{1}{\sum_{j=1}^{c} \left(\frac{\|x_k - v_i\|}{\|x_k - v_j\|} \right)^{2/(m-1)}} \tag{2}$$

According to [10] the quality of the FCM solution depends on the choice of the number of clusters, c. In this work the Xie-Beni index [12] was used to find the value of c that minimizes the FCM cost function (1). The results obtained from the FCM algorithm are presented in two vectors, one containing the cluster centers v_i and another containing the degree of membership μ_{ik}. From the latter it is possible to obtain continuous membership functions for rules antecedents based on Gaussian function approximation [13]. With this procedure, Gaussian type-1 fuzzy sets, centered at clusters center, are generated.

Here, an interval type-2 fuzzy set for the antecedent in each rule must be defined. One way to achieve this goal is to use the FCM algorithm with two values for fuzziness exponent (m_1 and m_2), resulting in two vectors of degrees of membership and two vectors of clusters centers. Then, a Gaussian function approximation using each cluster center as median is applied in the corresponding vector of membership degrees. According to [14], with this procedure two standard deviations, resulting in a "two-sided" Gaussian interval type-2 fuzzy set, are obtained to represent the T2FS with better accuracy.

TABLE I
PATTERNS DATA POINTS.

Pattern	0	1	2	3	4	5	6	7	8
Hours	8	4	7	1.6	4	4	2	4	4
Data Points	954	482	844	194	482	482	241	482	482

IV. IFDD SYSTEM

In a GPU the gas delivered to consumers is pumped through an alternative SGC compressor. This alternative machine presents high vibrations and one of the parts that can be affected by this vibration are the temperature instruments used to detect high temperature values and avoid mechanical damage in the machine cylinders. The vibrations often cause breaks in the temperature instruments triggering false alarms that trip the SGC and causes the shutdown of the entire unit. The IFDD system proposed and presented in this work has the purpose to detect these false alarms and prevent undesired SGC trips.

Analyzing the data from the temperature instruments it was identified nine patterns, one representing the normal state (no-fault state) and eight patterns of fault state. The fault state was subdivided in two types of faults, namely, bias state (with two patterns) and broken state (with six patterns).

To extract the rules that will compose the knowledge base of the IFDD system we used a sample of process history data associated to each pattern, comprising a total period of 39 hours of operation. Each sample contains data points with a sampling period of 30 seconds. Table I presents the total period (in hours) of the sample associated to each pattern and the sample size in each case.

The patterns for each state are presented in Fig. 3 to 11. The normal state is characterized by a temperature range of operation between about 75°C and 95°C (Fig. 3). Temperature values between 100°C and 140°C are associated to sensor bias as shown in Fig. 4 and 5. The span range of the instrument is 0°C to 200°C and temperature values above 160°C trigger the high-high alarm, tripping the SGC.

Fig. 6 to 11 show patterns of broken sensors. Fig. 6 and 7 show broken sensors with readings near 0°C and 200°C, respectively. Both sensors are faulty, since temperature values never reach these extremes. Fig. 8 and 9 show disperse readings indicating a situation where the instrument is broken but the SGC vibrations interfere with instrument signal transmission and produce a lot of noise. Fig. 10 and 11 present patterns that characterize a common situation of broken instrument with readings at 0°C or 200°C.

After selecting the patterns, the IT2FL system was structured comprising 20 antecedents and one consequent for each rule. The fuzzy operations used were max-product composition, product implication and centroid type-reduction. The

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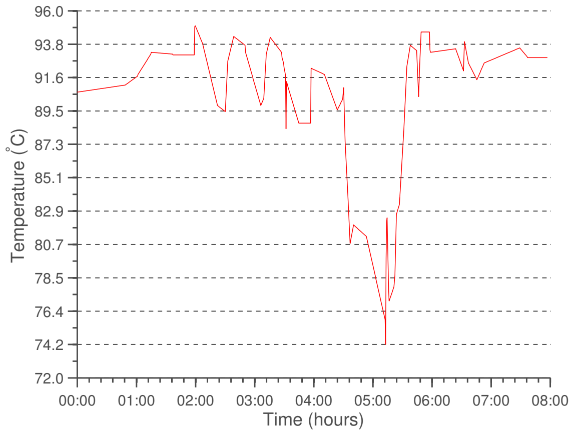

Fig. 3. Pattern 0 - Normal state.

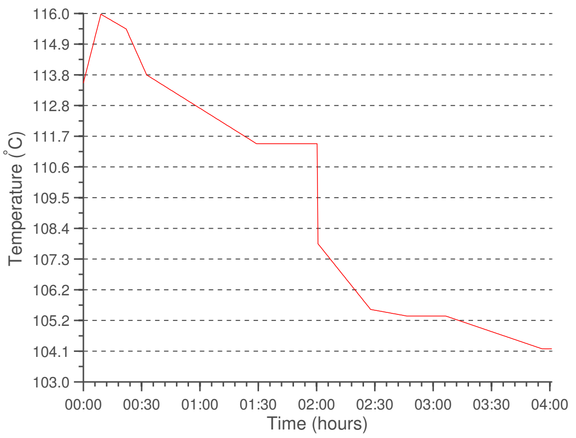

Fig. 4. Pattern 1 - Bias state

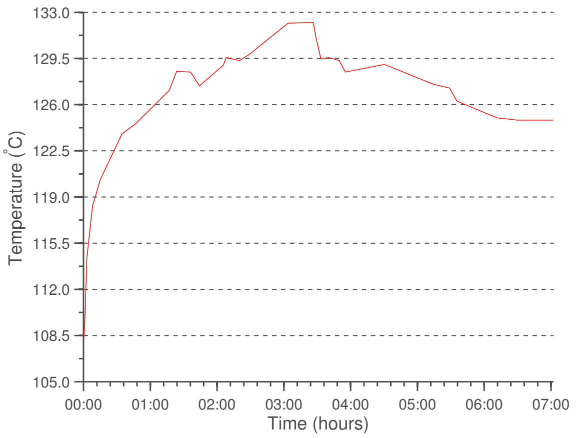

Fig. 5. Pattern 2 - Bias state.

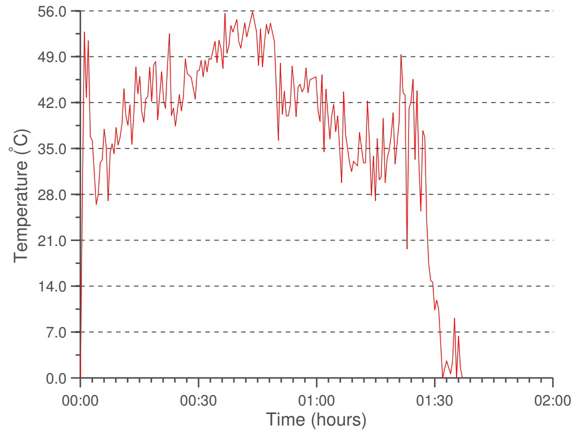

Fig. 6. Pattern 3 - Broken state.

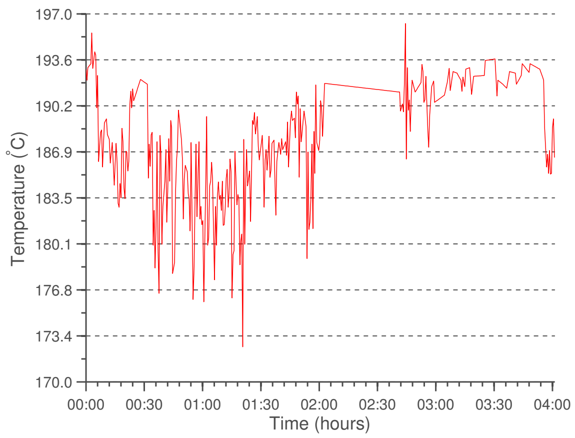

Fig. 7. Pattern 4 - Broken state.

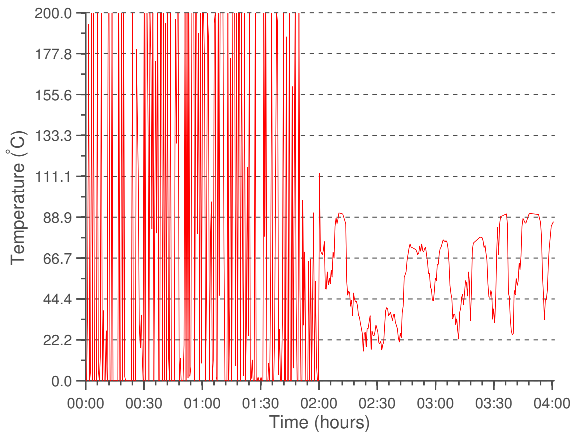

Fig. 8. Pattern 5 - Broken state.

only difference from the classical FL system is the rule aggregation that was not used. Following [15], the "winner takes all" strategy was adopted where the output of the fuzzy classifier is the class of the rule with the highest degree of activation.

The number of clusters (Table II) and consequently the number of rules was determined using the Xie-Beni index, using fuzziness exponent values $m_1 = 1.5$ and $m_2 = 3.0$. The FCM algorithm was computed twice, once for each fuzziness exponent. Four vectors were obtained from FCM, two related to the clusters centers and the others related to the respective degrees of membership. Two-sided Gaussian functions were generated providing the Interval Type-2 Fuzzy Set for each rule antecedent.

TABLE II
PATTERNS WITH NUMBER OF CLUSTERS AND CORRESPONDING CLASSES.

Pattern	0	1	2	3	4	5	6	7	8
Cluster Number	7	2	3	8	9	4	4	4	4
Class	0	1	1	2	2	2	2	2	2

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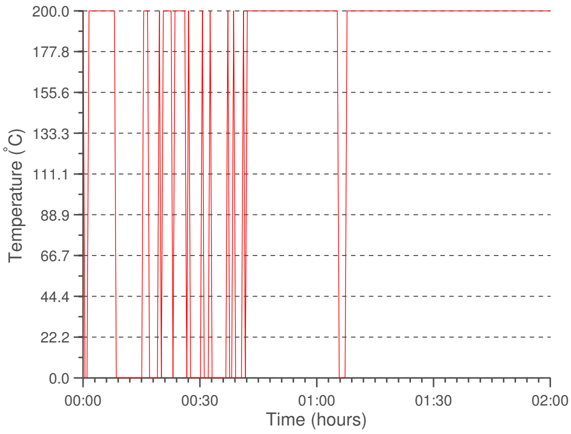

Fig. 9. Pattern 6 - Broken state.

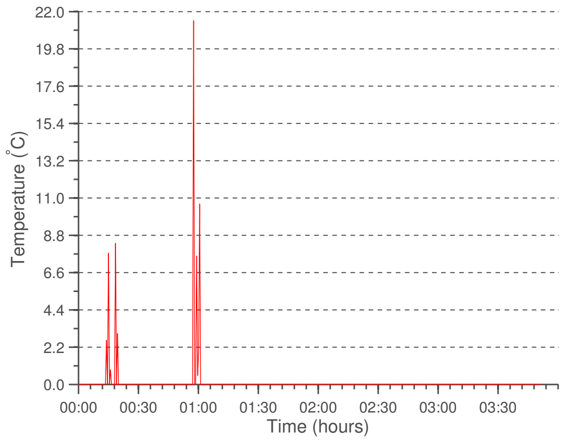

Fig. 10. Pattern 7 - Broken state.

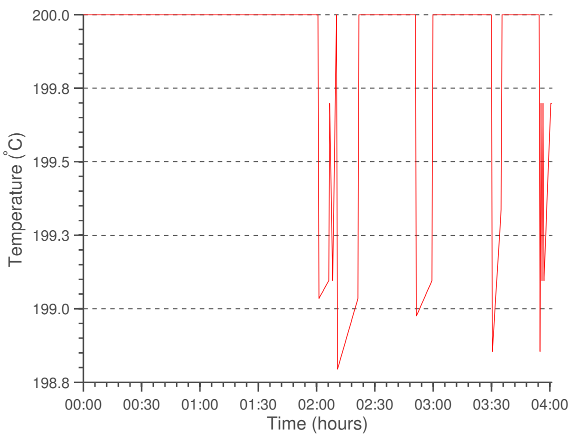

Fig. 11. Pattern 8 - Broken state.

The consequent part for each rule is represented by a type-1 triangular membership function with a universe of discourse [0; 2]. Three linguistic variables (or classes) were considered for the consequent and the respective parameters (position of the vertices of each triangular membership function) are shown in Table III.

In order to test the performance of the IFDD system the "leaving-one-out" error method [16] was adopted. This is a well-established strategy based on the "cross-validation" methods [17]. The error rate is defined as the ratio between

TABLE III
CONSEQUENTS CLASSES, PARAMETERS AND LABELS.

Class	0	1	2
Label	Normal	Bias	Broken
Parameters	[0, 0, 0.5]	[0.5, 1.0, 1.5]	[1.5, 2.0, 2.0]

the number of wrongly classified points and the total number of data points (sample size). Table IV summarizes the results of the simulation tests.

TABLE IV
PATTERNS ERROR RATE.

Pattern	0	1	2	3	4	5	6	7	8
Error	4.30%	7.47%	0.83%	0.00%	0.00%	0.42%	0.00%	0.00%	0.00%

The IFDD system presented an error of 4.30% in the classification of situations of pattern 0 (normal state). In these cases the IFDD system triggered false alarms of broken state. On the other hand, for patterns 1 and 2 (bias states) the IFDD system classified as broken 7.47% and 0.83% of the data, respectively, when it should be classified as bias.

The most challenging pattern was number 5 (broken state) due to its behavior (see Fig. 6). In this case, the IFDD system detected correctly 99.58% of the data, returning as normal only two of these data (0.42%).

V. CONCLUSION

In a GPU each SGC trip implies in at least two hours of shutdown until the SGC system can be restarted, which represents a cost of thousands of dollars for the company. This work shows the potentiality, simplicity and viability of a fuzzy inference system using only interval type-2 fuzzy sets to instrument fault detection and diagnosis. The IFDD system developed can be applicable and useful for a variety of real-world systems.

Real data of a commercial gas plant were used as a case study and the IFDD system presented a good performance in the prediction of eight different patterns, without the application of any tuning method. Notably, the worst result was an error of 7.47% (pattern 1) in a situation where a misclassification can occur without tripping the SGC.

Further improvements can be done applying genetic algorithm for optimization of fuzzy sets parameters or using artificial neural networks to build a self-evolving system.

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