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Fault Detection Using Fuzzy Similarities

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Abstract: A novel and global strategy involving fuzzy logic is presented and validated for an industrial wood dryer. The approach suggested is based on fuzzy similarities. Initially, the system requires an offline preparation where the fault origins and type are identified and using similarity conditions and IF-THEN diagnosis rules are designed. Finally, on-line the malfunction is detected and diagnosis. The fault detection scheme has an efficiency of 98%.

Key words: Fault detections, dryer, fuzzy logic, control process, fuzzy similarities

INTRODUCTION

The terms fault, failure and malfunction have many connotations in the literature as well as in general usage[1]. We will use the words fault and malfunction in relation to equipment as synonyms to designate the departure from an acceptable rage of an observed variables or calculated parameters associated with the equipment. Ulerich[2] reported the first attempt to perform fault diagnosis on the basis of fault trees. Different approaches for fault detection, diagnosis and isolation by mathematical models were developed in the last 20 years[3]. Recently, the application of the fuzzy logic to industrial level has been incorporated; although no formal methods to identify the fuzzy inference rules exist. Terptra[4] used an implicit fuzzy model (a fuzzy rule base) to analyse quantitative statements of the differences between the actual values and those predicted by quantitative models of the behaviour of the system with and without faults. Schneider (Schneider, 1994) and Sauter[5] describe similar observer based fault detection schemes in which fuzzy rules adapt the threshold for evaluating the residuals according to the current operating conditions. Ulieru[6] identifies faults using a fuzzy inter-relational diagnostic model which is constructed from fuzzy relations based on expert opinion that symptoms to faults. Incorporated a systematic fault diagnosis process using fuzzy diagnosis. The method consisted in studying the occurrence order of observable symptoms caused occurrence by fault origin is derived accordingly and then encoded into a set of IF-THEN diagnosis rules. Isermann[3] explained as a fuzzy logic approach can be applied to fault diagnosis with approximate reasoning on observed symptom. The possibility of each fault given the detected symptoms is calculated and the diagnosis is based on fuzzy pattern recognition. Fault detection and diagnosis essentially are tasks of pattern recognition[7]. Sensor (and other) data, which contain no readily discernable message, can be transformed via pattern recognition into clear-cut information useful for decision-making. Since artificial intelligent classify data effectively, it would seem that an artificial neural network or fuzzy logic would be an appropriate tool to try for fault diagnosis in process plants. On line fault detection and diagnosis are particularly desirable. Incipient fault detection, i.e, detection at the earliest possible stage, is the desired goal. In the face of increasing complexity and automation plants, achieving this objective requires effective, economical techniques. In this article the following specific objectives will be covered:

- Development a fault diagnosis strategy based on fuzzy similarities
- Test the new method using a wood dryer
- Identify the type of fault and establish the association of fuzzy similarities

Similarity in fuzzy set theory: Similarity is perhaps the most frequently used, most difficult to quantify and the most universally employed type of compatibility measure. The most common definitions "the similarity of two simple qualities may consist in the slightness of the difference that exists between them". A fuzzy measure of similarity is used to calculate the belief that the fault condition associated with each of the reference models has occurred in the real plant. Similarity indices measure

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the similarity between two fuzzy sets and require a greater degree of agreement. For crisp sets, sets X and Y are deemed completely similar if and only if their symmetric difference is the empty set. That is, if the sets are identical. Complete dissimilarity occurs when the symmetric difference is the union of X and Y[9].

The equality of two fuzzy sets A and B can be assessed by calculating the degree to which $A \subset B$ and $B \subset A$[9]. One measure of the grade of equality or similarity Sim_{AB} of A and B is given by

$$Sim_{AB} = \frac{\sum_{i=1}^{N} MIN[\mu_A(i)\alpha\mu_B(i), \mu_B(i)\alpha\mu_A(i)]}{MAX\left[\sum_{i=1}^{N}\mu_A(i), \sum_{i=!}^{N}\mu_B(i)\right]} \quad (1)$$

where μ_A is the membership function for fuzzy set A, μ_B is the membership function for fuzzy set B, α is the fuzzy inclusion operator:

$$\begin{cases} \mu_A(i)\alpha\mu_B(i) = 1 & \text{if} \quad \mu_A(i) \le \mu_B(i) \\ \mu_A(i)\alpha\mu_B(i) = \mu_B(i) & \text{otherwise} \end{cases} \quad (2)$$

and N is the number of elements defined on the discrete universe of discourse. The similarity measure can be simplified when the fuzzy sets are generated from measure data, since exact equality $\mu_A(i) = \mu_B(i)$ is unlikely with occur in practice. In this case,

$$Sim_{AB} = \frac{\sum_{i=1}^{N} MIN[\mu_A(i), \mu_B(i)]}{MAX\left[\sum_{i=1}^{N}\mu_A(i), \sum_{i=!}^{N}\mu_B(i)\right]} \quad (3)$$

This disagreement is necessary for a similarity measure to produce values throughout the range[1]. We start the discussion with the creation of cluster by assuming that knowing from experimental measurements whether a process is either operating satisfactory or not and if not, what causes the faulty performance. The classification of the state of the process according to similarities requires quantitative definitions. Tversky[9] noted that "most theoretical and empirical analyses of similarity assume that objects can be adequately represented as points in some coordinate space and the dissimilarity behaves like a distance function". For fuzzy sets, the distance is not between points but rather between membership functions as depict the Eq. (3). The points from states of the process in the same category, as for example "normal operation" will tend to cluster in the same region of this space. For example if there are two measurements x_1 and x_2 clusters as shown in the Fig. 1 might appear.

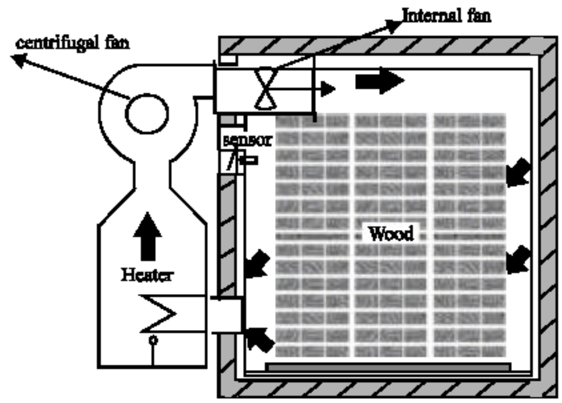

Fig. 1: Wood dryer

A set of measurements of n variables from the process can be though of as a point in n-dimensional space[1] and[11]. While a clear-cut division into well-defined crisp groups is called a partition, groups with uncertain boundaries in a fuzzy division are denoted clusters. Fuzzy clustering is a technique used to group a set of data into clusters such that elements within the same cluster have a high degree of similarity, while elements belonging to different clusters have a high degree of dissimilarity. A variety of fuzzy clustering methods have been proposed. The application of any fuzzy clustering method requires:

- Training set of measured data samples
- Choice of how many clusters to employ
- Method to compute cluster centers
- Criterion to evaluate the fuzzy model

In this article, we will describe a modification of Fuzzy C-Means (FCM) method. This is an iterative method introduced by Bezdek[12]. The algorithm is as follow:

- Select the number of faults as an initial partition matrix $U^{(0)}$

$$U^{(t=0)} = \begin{bmatrix} \mu_{11} & \mu_{12} & \cdots & \mu_{1n} \\ \mu_{21} & \mu_{22} & \cdots & \mu_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ \mu_{c1} & \mu_{c2} & \cdots & \mu_{cn} \end{bmatrix}$$

μ_{ik} is a membership value of sample point k in cluster i

- The similarity is measured using the equation (3)

$$Sim_{AB} = \frac{\sum_{i=1}^{n} MIN[\mu_A(i), \mu_B(i)]}{MAX\left[\sum_{i=1}^{n}\mu_A(i), \sum_{i=!}^{n}\mu_B(i)\right]}$$

In this case, the set A represents the fault used as references based on the operator experience and B represents the real fault in the equiptment in a particular time

- Compute the cluster centers per fault $(t)v_i^{(t)}=[v_{i1}^{(t)}\ v_{i2}^{(t)}\ \dots\ v_{im}^{(t)}]$ for i=1, 2, …, c, using the expression:

$$v_{ij}^{(t)}=\frac{\sum_{k=1}^{n}(\mu_{ik}^{(t)})^2\cdot x_{kj}}{\sum_{k=1}^{n}(\mu_{ik}^{(t)})^2} \tag{4}$$

j denotes the *j*-th coordinate of the *m*-dimensional points (*j*=1,2,…,*m*)

- Compute the distances from each element in the set to each cluster center, using

$$d_{ik}^{(t)}=\left\|\mathbf{x}_k-\mathbf{v}_i^{(t)}\right\|=\left[\sum_{j=1}^{m}(x_{kj}-v_{ij}^{(t)})^2\right]^{1/2} \tag{5}$$

for all clusters i=1, 2, …, c and points k=1, 2, …, n.

- Update the membership value of each data point. The updated values μ_{ik} of element *k* in cluster *i* are computed by the formula:

$$\mu_{ik}^{(t+1)}=\frac{1}{\left[\sum_{j=1}^{c}\left(\frac{d_{ik}^{(t)}}{d_{jk}^{(t)}}\right)^{2/(w-1)}\right]} \tag{6}$$

The special form of this formula ensures that the sum of membership values of an element over all clusters equals unity. In case some distance $d_{jk}^{(t)}$ in the denominator is zero (or extremely small in a computational sense), take $\mu_{jk}^{(t+1)}$ (for j≠i) and $\mu_{ik}^{(t+1)}$ (for j=i). Such a case corresponds to element x_k coinciding with the cluster center $v_i^{(t)}$. The partition matrix $U^{(t+1)}$ is then re-computed with these updated membership values as:

$$U^{(t+1)}=\begin{bmatrix}\mu_{11}^{(t+1)} & \mu_{12}^{(t+1)} & \cdots & \mu_{1n}^{(t+1)}\\ \mu_{21}^{(t+1)} & \mu_{22}^{(t+1)} & \cdots & \mu_{2n}^{(t+1)}\\ \vdots & \vdots & \ddots & \vdots\\ \mu_{c1}^{(t+1)} & \mu_{c2}^{(t+1)} & \cdots & \mu_{cn}^{(t+1)}\end{bmatrix} \tag{7}$$

- The iterative process stops when it has converged under some selected norm; otherwise, a new iteration is performed (set *t*=*t*+1 and return to step 2).

The norm employed for checking convergence might be:

$$\max_{i,k}\left|\mu_{ik}^{(t+1)}/\mu_{ik}^{(t)}\right|\le\varepsilon \tag{8}$$

where ε is a predefined accuracy level, say 1.0

In practice, some of the fault conditions may have common symptoms at some operating points then reference models were created using the experience of the operators. Thus each reference model is associated with a measure for avoid ambiguous situations. The measure of belief (bel) in the system being in one or more operating states is the sum of the basic assignments for all subsets of that combination of operating states. The plausibility (Plau) of the system being in one or more operating states is equal to one minus the sum of all the belief committed to the system being in any of the other operating states. The fuzzy fault model is made up from IF THEN rules, which describe the symptoms of faulty and fault-free operation in terms of predefined fuzzy reference sets. A particular model is defined by specifying the values of the elements of its associated fuzzy relational array. Each element of the array is a measure of the credibility or confidence that the associated rule correctly describes the behaviour of the system around a particular operating point. The models can be based on expert knowledge or learned offline from training data produced by computer simulation of typical plant, with and without the faults.

RESULTS

The strategy mentioned earlier was tested in the wood dryer as illustrate the Fig. 2. The experimental equipment works between 82.5°C and 93°C, depending on the drying schedule and the species of wood. The ventilating fans inside are installed between the trusses and are aluminium built. The heating system works with hot water to 96°C and the tubes are made of stainless steel. The flow of the heating system is controlled by modulating valves with a signal 4-20 mA coming from control system. A psychrometer with a thin PT100 (diameter 2.2 mm) was installed. The instrument was calibrated before the test period both for temperature and humidity measurements. The test consisted of continuous temperature and relative humidity measurement in the wood dryer for 2 months.

For to obtain a good system in a real-world environment is important to consider the following aspects[10]:

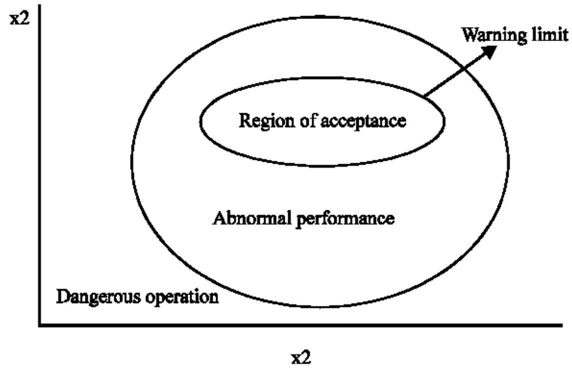

Fig. 2: Range of acceptable performance

Table 1: Fault modes in the dryer

No.	Failure mode	Number of faults in two months
1	Control valve for air not fully open	25
2	One fan stopped	20
3	Control valve for gas not fully open	14
4	psychrometer cannot read the information	3
5	Two fans stopped	9
6	Outlet air relative humidity low	8
7	Outlet air relative humidity high	4
8	PT 100 element fault	15
9	Leakage in gas valve	11

Table 2: Membership of fault

Fault	Segments	u_f	σ_f	Primary fuzzy sets
1	[-1.0, 0.2]	-0.8	0.3	LOW
	[0.2, 0.6]	0.05	0.3	ZERO
	[0.4, 1.0]	0.5	0.2	HIGH
2	[-1.0, 0.2]	-0.77	0.32	LOW
	[0.2, 0.6]	0.1	0.28	ZERO
	[0.4, 1.0]	0.55	0.21	HIGH
3	[-1.0, 0.2]	-0.77	0.33	LOW
	[0.2, 0.6]	0.05	0.33	ZERO
	[0.4, 1.0]	0.43	0.31	HIGH
4	[-1.0, 0.0]	-0.4	0.2	LOW
	[-0.2, 0.7]	0.5	0.2	ZERO
	[0.2, 1.0]	0.6	0.2	HIGH
5	[-1.0, 0.1]	-0.8	0.3	LOW
	[0.2, 0.7]	0.2	0.2	ZERO
	[0.4, 1.0]	0.5	0.2	HIGH
6	[-1.0, 0.2]	-0.8	0.3	LOW
	[0.2, 0.6]	0.05	0.3	ZERO
	[0.4, 1.0]	0.5	0.2	HIGH
7	[-1.0, 0.1]	-0.3	0.3	LOW
	[0.1, 0.5]	0.4	0.4	ZERO
	[0.5, 1.0]	0.8	0.2	HIGH
8	[-1.0, 0.3]	-0.8	0.3	LOW
	[0.1, 0.6]	0.2	0.2	ZERO
	[0.3, 1.0]	0.5	0.2	HIGH
9	[-1.0, 0.3]	-0.8	0.3	LOW
	[0.2, 0.6]	0.05	0.2	ZERO
	[0.3, 1.0]	0.5	0.2	HIGH

- The user should define distinctive rule-bases for different situations during workdays. These rule-bases are processed independent of each other corresponding to the current situation. The task of the user is to inform the system about the current situation. Besides, the user should be able to instruct the system not to adapt the current rule base. This enables a single modification of the current temperature without modifying the rule-base permanently.
- The rule-base must consist of a suitable number of rules. It can be shown that if the number of rules isn't restricted, in the case that the rule base consists of to few rules, the system has convergence problems.

It is clearly not possible here to catalog all type of faults and their expect occurrences. Deviations from process operating specifications can be categorized in terms of the particular deviations. The Table 1 shows the type of faults considered in this article. Unfortunately, there is not an extensive data bank of information on the types of faults; the Table 1 is a product of our own research and the collaboration of the wood dryer operators.

In the dryer the input variables are: Airflow, internal fan velocity, gas flow and the output variables are: air temperature, absolute humidity, water temperature. The range of input and output variables are covered by a fuzzy set of 3 functions Low,Zero,High.

The If-THEN rules, which describe symptoms of correct operations, are:

IF airflow is low THEN humidity is high (credibility 1.0)
IF airflow is high THEN humidity is low (credibility 1.0)
IF airflow is zero THEN humidity is zero (credibility 1.0)
IF gas flow is low THEN water temperature is low (credibility 1.0)
IF gas flow is high THEN water temperature is high (credibility 1.0)
IF gas flow is zero THEN water temperature is zero (credibility 1.0)
IF gas flow is low AND airflow is high THEN air temperature is low (credibility 1.0)
IF gas flow is high AND airflow is low THEN air temperature is high (credibility 1.0)
IF internal fan velocity is low THEN humidity is high (credibility 1.0)
IF internal fan velocity is zero THEN humidity is zero (credibility 1.0)
IF internal fan velocity is high THEN humidity is high (credibility 1.0)

And the symptoms of faulty operation are described by:

IF airflow is low THEN air temperature is high (credibility 0.5)
IF airflow is high THEN humidity is low (credibility 0.5)

Table 3: Similarity of measured fault as for to the detected fault for the fault monitor

Measured /detected	1	2	3	4	5	6	7	8	9
1	0.997	0.000	0.000	0.001	0.001	0.000	0.000	0.000	0.000
2	0.005	0.991	0.000	0.005	0.002	0.001	0.002	0.002	0.002
3	0.008	0.000	0.998	0.000	0.000	0.000	0.001	0.002	0.001
4	0.006	0.000	0.002	0.990	0.000	0.000	0.000	0.001	0.001
5	0.000	0.001	0.003	0.002	0.999	0.000	0.002	0.002	0.002
6	0.001	0.000	0.000	0.005	0.000	0.992	0.000	0.002	0.003
7	0.001	0.000	0.000	0.000	0.000	0.002	0.995	0.995	0.996
8	0.001	0.001	0.000	0.000	0.000	0.002	0.996	0.996	0.997
9	0.001	0.000	0.000	0.001	0.001	0.001	0.995	0.995	0.996

Table 4: Results in operating conditions

	Fault number								
Cluster	1	2	3	4	5	6	7	8	9
Acceptable performance									
Mean	0.45	0.55	0.55	0.50	0.60	0.66	0.52	0.54	0.61
Standard deviation	0.02	0.03	0.01	0.08	0.02	0.02	0.04	0.01	0.03
Abnormal performance									
Mean	-0.4	-0.3	-0.6	1.0	0.72	0.78	0.87	0.81	0.69
Standard deviation	0.02	0.02	0.04	0.09	0.07	0.09	0.06	0.07	0.04

The initial partition of matrix *U* is the Table 2. The partition of the continuous universe requires a priori knowledge of the input/output space. In the Table 2 a functional definition expresses the membership function in a triangle shaped function. The functional definition can readily be adapted to a change in the universe. The functional definition was expressed as

$$\mu_f = \exp\left[\frac{-(x - u_f)^2}{2s_f^2}\right] \tag{9}$$

In the design of fault detection system, the noise uses to generate false alarms, for avoid it, anti-noise filter was installed in the pilot plat, however the noise uses to be very low. The Table 3 resumes the degree of accuracy of the method. This table depicts as the detected fault and measured fault are compared. The faults were produced for the operator, thus that the type of fault was known previously. The response of the system was compared with the real-data and the result is depicted in the Table 3. This table shows as the degree of accuracy of the system, when the value is close to 1.0 (see equation 8), the fault was detected. In this work the data collected to establish the faults is not shown for it is too voluminous but Table 4 list the mean (membership function value) and variance (ó) for each fault (assuming the distributions were uncorrelated and Gaussian). The Tables 3 and 4 confirm that the symptoms of fault are distinguishable from those of correct behaviour at many operating points and over the restricted operating range when the fault is present, only the fault type 2 could there be any possible question about the classification. As mentioned earlier, all faults were evaluated and combinations of them were considered as well. The detector worked well, all faults were detected and the system does not confuse symptoms with faults, see Table 4. Traditionally, the operator has to locate the fault by himself, thus the provision of the fault detector allows detecting the malfunction and reduce the downtime without incurring any additional costs except computer costs.

CONCLUSION

The artificial intelligent exhibits a number of features that make them attractive for control, fault detection and diagnosis in complex systems. With fuzzy logic, we can make the correct associations between system faults and vectors of measurements. Moreover, it can accommodate its diagnosis to the noise and uncertainly that exist in all process measurements. The methodology proposed in this work was applied to a wood dryer. It is rapid and accurate. The scheme is computationally efficient and the results have depicted that the scheme can successfully diagnoses correct operation in a dryer. The descriptions provided in this article including enough details for possible used in other type of equipments or other type of dryers.

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