Nonlinear Residual Generator Design Through Fuzzy Clustering For Process Fault Detection in a Co-current Heat Exchanger

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Abstract: In this paper, a fuzzy model-based algorithm is developed for leak detection in a pilot heat exchanger. A dynamic fuzzy model is first derived from input-output measurements using a fuzzy clustering technique. This model is run in parallel to the process for residual generation. The detection scheme has been tested and validated using real data from a co-current heat exchanger, and has proven to be efficient in detecting leaks of different magnitudes in the water circulation pipe of the water circuit.

Key words: Leak detection, fuzzy models, fuzzy clustering, heat exchangers.

INTRODUCTION

Fault detection and diagnosis are playing an increasing important role in process industries. Heat exchangers are important components in power, chemical, oil refinery industries and in other areas. A common heat exchanger faults are tube leaks due to aging and thermal stress. Early and accurate detection of such faults in operation mode is a major task for any FDI system development. This may help in reducing possible damage to equipments and productivity loss, and consequently ensures safety for operators.

Heat exchanger tube and pipe leaks are a special type of process faults which belong to the class of gross error problems. Most methods for gross error estimation use statistical analysis [GAR 00] [PAT 01] and system identification methods [GER 88][ISER 84][PAT 01]. However, satisfactory performance of the above model-based approaches can only be achieved if dynamic reliable models with known properties and accumulated operational experience are available. From a modeling point of view and depending on the operation mode, heat exchangers are complex systems involving various disturbances, nonlinearities and time-varying characteristics. The use of first-principle based models allows better understanding of the process behavior and then a greater depth in diagnosis, due to the interpretable parameters. However, dynamic models of heat exchangers are difficult to derive by theoretical modeling since the underlying physical effects are quite complex and a huge number of physical parameters such as heat transfer coefficients are unknown.

Since leak faults exhibit non negligible effects on the heat exchanger behavior, we strongly need to use nonlinear dynamic models that should cover a wide operating range of the physical plant instead of steady-state models. This may enhance the robustness and the effectiveness of the model-based FDI mechanisms. The development of such models from physical laws and/or from measurements is still of substantial interest [BAL 97][BAL 99][BAL 00][PEN 97][PER 05]. The high priority devoted to these complicated faulty situations that are frequently encountered in practice motivated us to investigate in this paper the use of fuzzy logic as a tool to cope with leak problems in heat exchangers. Our main contribution consists in the design and the implementation of an effective fuzzy model-based leak detection scheme for a pilot heat exchanger. For this purpose, a fault-free dynamic fuzzy model of the heat exchanger is developed using a set of input-output measured signals. The structure in the collected data is determined using fuzzy clustering technique. This fuzzy model is then involved in a fault diagnosis scheme to detect leaks in the water circulation pipe of the pilot heat exchanger.

1. Process description

The process under investigation is a co-current heat exchanger which is the main part of the pilot plant depicted in Fig. 1. It consists of three subsystems: the heater, the air circuit and the water circuit. In more details, the system is composed of an electric heater of the air, pipes for air and water
circulation, a co-current gas-liquid exchanger, two valves to control the portion of the air flow which is recycled and the portion which is evacuated, and a variable speed pump to control the water flow. The water entering the heat exchanger with the temperature $T_{33}$ [20-30°C] is heated up to the temperature $T_{34}$ [25-100°C] with hot air. The amount of air coming from the electric heater with temperature $T_{14}$ [25-200°C] enters the heat exchanger with the temperature $T_{16}$ [30-100°C] after flowing through the air circulation pipe. Total or partial recycling of air can be considered depending on the position of the two valves. This allows emphasizing different operation modes of the heat exchanger in the experimental study.

The following variables can be measured:

- $P$: the heating power [KW];
- $T_{14}$ and $T_{16}$: the air temperature, respectively, after the heater and before the heat exchanger [°C];
- $T_{33}$ and $T_{34}$: the water temperature, respectively, at the first third length and the outlet of the heat exchanger [°C];
- $Q_a$: the air flow rate [m$^3$/s];
- $Q$: the water flow rate [m$^3$/s].

In order to detect leak faults in the water circulation pipe of the heat exchanger, we need to find a supervision scheme for some relevant measured variables based on model equations and no additional sensor signals.

2. Takagi-Sugeno fuzzy models

Fuzzy identification aims at finding a set of fuzzy IF-THEN rules with well defined parameters that can describe the given input-output behavior of the process. A large class of multi-input single-output (MISO) nonlinear dynamic processes can be described by a nonlinear autoregressive with exogenous input (NARX) model, which gives the mapping between the input-output data and the predicted output of the model:

$$y(k) = f(u_1(k-1), \ldots, u_r(k-1), \ldots, u_1(k-n_u), \ldots, u_r(k-n_u), y(k-1), \ldots, y(k-n_y)) \quad (1)$$

where $u_1, \ldots, u_r$ denote the model inputs and $y$ the model output. The integers $n_u, \ldots, n_u$ and $n_y$ represent the dynamic orders of the inputs and the output, respectively.

Throughout this contribution, the unknown function $f(\cdot)$ in (1) is approximated by a dynamic Takagi-Sugeno (TS) fuzzy model which is characterized by rule consequents that are linear functions of the input variables [CAO 97].

![Figure 1. Schematic picture of the heat exchanger.](image)

The fuzzy rule base comprises $c$ IF-THEN rules of the form:

$$R^i: \text{If } x_1 \text{ is } A_{i1}^1 \text{ and } x_2 \text{ is } A_{i2}^1 \text{ and } \ldots \text{ and } x_n \text{ is } A_{in}^i \text{ Then } y^i = a_{1i}^i x_1 + \ldots + a_{ni}^i x_n + b_i \quad (1 \leq i \leq c) \quad (2)$$

where the vector $x(k) = [x_1(k), x_2(k), \ldots, x_n(k)]^T$ contains subsets of the process input and output variables and $A_{ij}, (1 \leq j \leq n)$, is a fuzzy set defined on the universe of discourse of the rule-premise variable $x_j$. The rule consequents represent affine difference equations which are linear in the parameters $a_{ij}$. The additional constants $b_i$ define the operating points.

Choosing the product operator as t-norm, the output of the fuzzy model with $c$ rules is aggregated as:

$$y = y^1 \sum_{i=1}^{c} \mu_i \frac{y^i}{\sum_{i=1}^{c} \mu_i} \quad (3)$$

where $\mu_i$ is the degree of activation of the rule $i$:

$$\mu_i = \prod_{j=1}^{n} \mu_{A_{ij}}(x_j), \quad (1 \leq i \leq c) \quad (4)$$

and $\mu_{A_{ij}}(x_j): \mathbb{R} \to [0, 1]$ is the membership function of the fuzzy set $A_{ij}$ in the antecedent of the rule $i$. 

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2.1. TS fuzzy model identification

The problem of fuzzy model identification is to determine the rule-premise and the rule-consequent parameters, i.e., the membership functions of the input variables and the parameters of the local linear models. Knowledge-based modeling is of big interest for fuzzy rules derivation but usually delivers only a rough idea of the process behavior. Therefore, a special attention has been devoted to data-driven modeling approaches which compute nonlinear dynamic fuzzy models from input-output measurement data, e.g., fuzzy clustering [BRU 96][GUS 79][ZHA 94], tree construction algorithms [BAL 99], or neuro-fuzzy techniques [AYO 95][FRA 96][GUS 79][ZHA 94], or applied to compute the fuzzy partition matrix $U$. The data set $Z$ to be constructed from the available data: the regression matrix $X$ and the output vector $y$ are regression vector components are chosen. The ordinary least-squares algorithm.

This local parameter estimation procedure can be seen as a special form of regularization [FIN 00].

3. Fuzzy modeling of the heat exchanger

From a throughout analysis of the variables described in Section 1 and based on prior knowledge, it can be concluded that for the purpose of water circulation pipe leaks detection, the most relevant variables are the heating power, $P$, the water temperature before the heat exchanger, $T_{16}$, and the water temperature after the heat exchanger, $T_{34}$. Therefore, we need to find a supervision scheme of these three measurements based on the following NARX structure:

$$T_{34}(k+1) = f(T_{34}(k), T_{16}(k), P(k))$$ (8)

where $f$ denotes a nonlinear dynamic function.

The task is now to identify a dynamic TS fuzzy model that is capable to approximate the nonlinear function $f$ over a wide operating range. For this purpose, real data from the pilot heat exchanger is generated in normal operation mode. During the experiment, the air flow rate $Q_a$ and the water flow rate $Q$ are kept constant. The heating power covers the complete operating regime from 0 to 10 KW. This variable represents the manipulated variable. Since we need to consider large variations of the process operating point, we used dynamic excitation in the heating power, $P$, by employing an amplitude-modulated pseudo-random binary signal. The following structure is chosen for the $i$th IF-THEN fuzzy rule:

$$\text{IF} P(k) \text{is } A^1_i \text{ and } T_{16}(k) \text{is } A^1_i \text{ and } T_{34}(k) \text{is } A^1_i \text{ THEN } T_{34}(k+1) = b^1_i + a^1_i P(k) + a^1_i T_{16}(k) + a^1_i T_{34}(k)$$ (9)

Then, the rule-consequent parameters are computed using a weighted ordinary least-square estimate. Let $\theta^T_i = [a^T_i, b_i]$; let $X_c = [X, 1]$ and let $W_i$ denote a diagonal matrix in $\mathbb{R}^{c \times c}$ having the degree of activation, $\mu_i(x(k))$, as its $i$th diagonal element. The local weighted least-squares solution is given by:

$$\theta_i = [X^T_c W_c X_c]^{-1} X^T_c W_c y$$ (7)

Given $Z$ and the estimated number of clusters $c$, the Gustafson-Kessel fuzzy clustering algorithm is applied to compute the fuzzy partition matrix $U$. The fuzzy sets in the antecedent of the rules are obtained from the partition matrix $U$ whose elements are the membership degrees of the data objects in clusters. When the shape of the antecedent fuzzy sets $A^1_i$ is given, their parameters are systematically generated through the iterative procedure of the Gustafson-Kessel algorithm. However, we can also obtain one dimensional fuzzy sets $A^j_i$ from the multidimensional fuzzy sets defined point-wise in the $i$th row of the partition matrix $U$ by projections onto the space of the input variables $x_j$ [GOM 99].

3.1. Identification results

The Gustafson-Kessel fuzzy clustering algorithm described in Section 2 is applied to the set of fault-free input-output observations which contains 2000 samples.
The number of clusters to be detected is \( c = 3 \), and as so, the heat exchanger fuzzy model has three rules. The premise heating power space portioning corresponds to the membership functions depicted in Fig. 2. These fuzzy sets are labeled as Small (S), Medium (M), and Big (B), and define three operating regions for the manipulated variable. Space partitioning of the two other premise variables into three regions is also achieved. Any further increase in the model complexity does not improve the model performance.

For validation, two tests have been realized. In the first validation test, the identified fuzzy model is run in parallel configuration to the real process using the same set of identification data. The second is a cross validation test where a second data set with similar excitation is employed. For evaluating the model performance the mean-square error index is used. The mean-square error for \( T_{34} \) prediction is about 0.0636 for the first test, and is about 0.0250 for the cross validation test. The resulting high model performance is shown in Fig. 3. These results reveal sufficient for fault detection purpose. Note that the parameters of the local linear models in the rule consequents are locally estimated from the identification data using equation (7).

4. The fuzzy leak detection scheme

The task of the designed water pipe leak detection scheme is to observe possible deviations of the actual heat exchanger behavior from the nominal one. The nominal behavior is derived from the dynamic fuzzy model (9). Significant symptoms appear as differences between the estimated water temperature \( \hat{T}_{34} \) and the measured water temperature \( T_{34} \). The water pipe leak faults are then detected and diagnosed by supervising the water temperature behavior. Therefore, the residuals are computed as:

\[
r(k) = T_{34}(k) - \hat{T}_{34}(k)
\]

These detection signals have the property of being approximately zero in normal (leak-free) situation and they deviate from zero if either measured signals or the process itself are faulty. Because of noisy measurements and disturbances, it is hard to detect the leak faults in the water pipe, in particular when the signal-to-noise ratio is small. Also, the water temperature is strongly affected by the water flow rate. This serves as a motivation for adopting our fuzzy model-based leak detection mechanism to ensure robust residual generation.

In order to detect faults and minimize false alarms, nonzero alarm thresholds should be set up. In this study, the thresholds are settled on the basis of several experiments with different leak faults magnitudes.

5. Experimental results

The results presented below correspond to the real-time implementation of the water pipe leak detection scheme designed for the co-current heat exchanger. A single pipe leak fault with magnitude 25, 30 or 40% is introduced. For each leak fault magnitude, an appropriate variable heating power signal is generated so that the safety of the whole equipment is to be guaranteed. Leak in the water circulation pipe is introduced using a bypass valve.

First, the performance of the leak detection scheme in healthy operating mode is investigated. Fig. 4(a) depicts the corresponding residual behavior for 2000 samples. One may notice that the residual signal reflects clearly the fault-free situation with staying at zero, or almost zero value because of measurement noises. For leak fault magnitude of 25% introduced at time instant \( t = 1900 \) s, the generated residual signal presents significant deflection after fault occurrence as shown in Fig. 4(b). The measured output temperature \( T_{34} \) and also the residual rise, because a smaller volume of water is heated up with the same amount of air. The same situation holds when 30 and 40% fault magnitudes are separately introduced at \( t = 1280 \) s and \( t = 580 \) s, respectively, as can be seen in Fig. 4(c) and Fig. 4(d). It is important to notice that the performance
of the detection scheme appears to be reasonable in these two tests, since the leak fault has been introduced during the transient phase of the residual signal. The integration of an adequate decision system the implemented fuzzy model-based leak detection scheme may improve its diagnosis capability.

6. Conclusion

In this paper, we provided an effective and efficient solution to leak detection problem in a concurrent heat exchanger. A fuzzy-model based fault detection and diagnosis scheme is designed using experimental data collected for the pilot plant. Leak in the water circulation pipe of the water circuit is considered with different magnitudes. The detection capability of the implemented algorithm is well justified through several experiments. The main advantage of the method is the use of a model that can be trained from measured data instead of applying complicated first-principles. This may allow considering different types of faults (sensor and actuator faults) and different operating regimes of the physical plant.

Future work will be focused on the use of an appropriate statistical-based decision system instead of simple thresholding logic, since the heat exchanger is in practice exposed to different types of faults that may be considered in a global approach for better diagnosis.

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