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NEURAL NETWORK BASED ON-LINE DETECTION OF FOULING IN A WATER CIRCULATING TEMPERATURE CONTROLLER (WCTC)

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INTRODUCTION

The main application of WCTC's is mould temperature control in the plastics industry. Depending on the raw material, the water temperature ranges between 60°C and 150°C. So fouling occurs, and some customers have to change the heat exchanger and/or the heater after only few months of operation. Nowadays, different techniques are available (ultrasound (e.g. Bott, 2000), temperature and heat flux measurements (e.g. Abu-Zaid, 2000)), but limitations exist mainly due to the fact that the number of sensors is limited. So, only localized fouling can be detected. A more global approach has been proposed (Prieto et al., 1999). It is based on the difference between the real system and its model. It can be shown that for heat exchangers that have a low *Ntu*, this technique detects only quite important fouling. Hence it is necessary to move to more complex supervision techniques.

After having theoretically shown that an auto-adaptive neural network is able to detect fouling in an electrical heater (Lalot and Lecoeuche, 2003), the aim of this paper is to present (using actual experimental data) the benefits of a new supervision architecture (Lecoeuche et al., 2004). This new architecture is an improvement of the architecture used in the previous work (Lalot and Lecoeuche, 2003). The aim of this system is to alert the customer before any significant degradation of the capabilities of the WCTC occurs. This is possible when using pattern recognition techniques. The latter are developed to supervise systems for which models are difficult to estimate using analytical techniques.

In the pattern recognition approach, a characteristic vector X_k, that represents the current functioning state, is extracted from the amount of process information. Then, using an adequate dataset, a learning procedure is used in order to obtain the n-dimensional map of the various functioning modes of the system. The diagnostic is eventually achieved by labeling the current state with its membership class. Here the difficulty is that, in case of fouling, the normal functioning mode slowly evolves with time.

This difficulty is curcumvented by using a specific supervision architecture allowing a continuous modelization of the functioning modes. The key idea is to use a classification neural network (Lecoeuche and Lurette, 2003) that continuously models functioning modes corresponding to the current functioning states of the system.

When fouling occurs in a WCTC, the model of the normal functioning mode deviates from its normal position. Hence, its representative parameters evolve. Some specific tools have been introduced into a monitoring stage, to detect and to analyze these evolutions.

After an overview of the supervision system which is presented in the first section, the second section presents the AUDyC neural network used to model evolutionnary modes. In the third part, two tools for fouling detection are introduced. The first one is dedicated to fast drift detection. This is equivalent to the detection of an "*observation drift*". The second one is dedicated to the detection of slow drifts or "*mode drift*". Finally, some results that come from real experiments on a WCTC, are presented in order to illustrate the reliability of the tools.

1. Overall presentation of the supervision system

The supervision system (Lecoeuche et al., 2004) that consists of three modules is developped to continously supervise an indutrial process. The three main modules work on line and communicate together to exchange information in a cyclic maner.

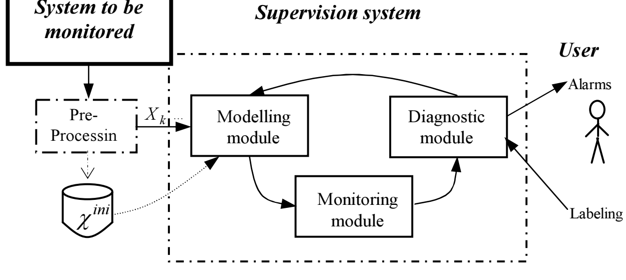

Fig. 1. : Presentation of the supervision system

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- The modelling module is the core of the system. The AUDyC network (Lecoeuche and Lurette, 2003) is chosen to achieve the modelization of the functioning modes. This choice is motivated by the fact that this network is developed to easily handle data acquired online.

- The second module, the monitoring module, is dedicated to the detection of the system functioning modes evolutions. Depending on the velocity of these evolutions, two kinds of system evolutions have to be detected: observation drift (fast evolution) and mode drift (slow evolution).

- The third module, the diagnostic module, is used to detect the location and the labels of the system failures. This is based on the analysis of the current functioning state membership degrees to known modes.

At last, the process user can communicate with the supervision system through the diagnosic interface.

2. AUDyC NN and dynamical modelling

The modelling module is built with the help of the AUDyC NN (Lecoeuche and Lurette, 2003). The structure of this network is very common: one input layer (*D* neurons), one prototype layer (*J* neurons) and one output layer (*I* neurons). Each neuron of the output layer represents a functioning mode. Each mode is defined by one or several gaussian models (prototypes). The membership degree μ_k^j of the characteristic vector X_k to the prototype P_j (defined by its center M_{Pj} and its covariance matrix Σ_{P_j}) is evaluated using equation 1:

$$\mu_k^j = \exp\left[-\frac{1}{2}(X_k - M_{P_j})^T.\Sigma_{P_j}^{-1}.(X_k - M_{P_j})\right] \quad (1)$$

To ensure a continuous adaptation of the network, the online learning process of the network consists of three stages:

- **First stage**: ''Classification''. The construction of the network is achieved by the creation or the adaptation of nodes (prototypes and/or modes).

The prototype creation is based on a distance rejection rule. For example, if a new characteristic vector X_k is not close to any existent prototype, a prototype is created with X_k as its center and Σ_{ini} as its initial covariance matrix. Otherwise, if the data is close to a prototype, the adaptation of this one is done iteratively thanks to recursive equations:

$$\begin{aligned} M_{P_j}^k &= M_{P_j}^{k-1} + \frac{1}{N}(X_k - X_{k-N+1}) \\ \Sigma_{P_j}^k &= \Sigma_{P_j}^{k-1} + \Delta X \begin{bmatrix} \frac{1}{N} & \frac{1}{N(N-1)} \\ \frac{1}{N(N-1)} & \frac{-(N+1)}{N(N-1)} \end{bmatrix} \Delta X^T \end{aligned} \quad (2)$$

with $\Delta X = \left[X_k - M_{P_j}^{k-1}, X_{k-N+1} - M_{P_j}^{k-1}\right]$; N is the prototype size

-**Second stage**: ''Fusion''. This stage comes to merge modes that are close in the representation space. In fact, after the classification stage, some of the prototypes share data but belong to different classes. This makes ambiguities that are treated during this phase.

-**Third stage**: ''Elimination''. This stage is used to eliminate modes with too few assigned data or that are obsolete.

Here is only given a brief overview of the AUDyC network. More information on the learning strategies are presented in (Lecoeuche and Lurette, 2003), (Lurette and Lecoeuche, 2003), and (Lecoeuche et al., 2004).

These three stages are carried out recursively. At the end of each iteration, information is sent to the monitoring module. These information consist of all the parameters of the functioning modes of the process under supervision.

3. Online monitoring tools

To be sure that the monitoring module is efficient, two tools are necessary. The first one is used for the detection of fast drifts. The latter correspnd to the displacement of the observations that does not lead to the modification of the functioning mode in the representation space. The second tool is used for the detection of slow drifts. This correspond to the displacement of the functioning mode. For this study, two assumptions are made :

- the normal functioning mode has a Gaussian distribution represented by only one mono-prototype class
- its label is known thanks to a prior knowledge.

Fast drifts detection tool

For the fast drifts, the main problem is to detect the drift of observations moving away from the current functioning mode. In this case, the observations do not modify the prototype that defines the normal functioning mode. Hence, the membership degree of the current observation to this particular prototype (eq. 1) decreases quickly. It is then necessary to get a tool which is able to allow for small variations of the membership degree and detect as soon as possible the drift.

A specialized tool, called "Generalized Cusum", has been developed. It estimates the sum of the cumulated errors between the current observation and the current normal mode P_1. It is based on a decision function g_k (with a threshold $\tau = \mu_{\min}$ fixing the membership bounds of the normal mode).

$$\begin{cases} g_0 = 0 \\ g_k = \max(0, g_{k-1} - Log(\mu(P_1, X_k)) - \tau) \end{cases} \quad (3)$$

If the samples move away from the "normal" model, the function g_k increases gradually up from zero. To avoid the detection of a drift when the membership degree value is notably biased by a measuring noise, a threshold h_f is determined for the decision function g_k is fixed. An observation drift is detected only when the value taken by g_k is higher than the detection threshold h_f. More details are found in (Amadou-Boubacar and Lecoeuche, 2005)

Slow drifts detection tool

In this case, as the evolution is slow (like fouling) the current functioning mode evolves according to (2). The objective of this tool is to detect if a deviation occurs and to inform towards which mode (known or unknown) the system moves. A specific tool has been developed (Berthier, 2004) and is based on the computation of drift rates.

To be able to compute a drift rate, it is necessary to compute the distance between two classes (e.g. the current one and the class corresponding to a failure mode), each being represented by a center and a covariance matrix. It has been shown that for the purpose of drift detection, the Kullback-Liebler distance is the most convenient (Zhou and Chellappa, 2004).

Then, the drift rate towards a known failure j is computed by

$$T_j = \frac{1}{m-1} \sum_{k=2}^{m} \frac{\Delta_j^k}{d_{Kullback}(M_k, \Sigma_k, Md_j, \Sigma d_j)} \quad (4)$$

Where $\Delta_j^k = d_{Kullback}(M_k, \Sigma_k, Md_j, \Sigma d_j) - d_{Kullback}(M_{k-1}, \Sigma_{k-1}, Md_j, \Sigma d_j)$
k, index on the set of the last "m" memorized current modes and j, index on the set of known failure modes.

Once each j^{th} component of the vector T is computed (one for each known failure except $j=0$ representing the current mode at the initial time t0), 2 values are determined :

$$Min = minimum(T_j) \text{ and } IndiceMin = argmin(T_j) \quad (5).$$

The slow drift decision function is based on these two values.

```
if Min < h_s (h_s is a negative threshold),
      <<Drift detection towards "IndiceMin">>
return
if (T_0 > 0.2*h_s)
      <<Drift detection towards "Unkown">>
return
Otherwise
      <<No drift>>
return
```

Alg. 1 : Slow drift decision rule

4. Application to the WCTC monitoring

The WCTC used for the experiments consists of a pump, a controller, an electric heater, an exchanger, a filter and connection pipes.

First of all, some characteristics (discriminating information) being sensitive to system deviations but less sensitive to the signals disturbances are selected to build the characteristic vector. It has been checked that the pressure losses ratios (local to total) are independent of the mass flow rates, of the heater electrical power, and of the load/sink demand. Figure 2 shows that these ratios (centered and normalized) make possible the discrimination of the drifts (each drift is carried out separately).

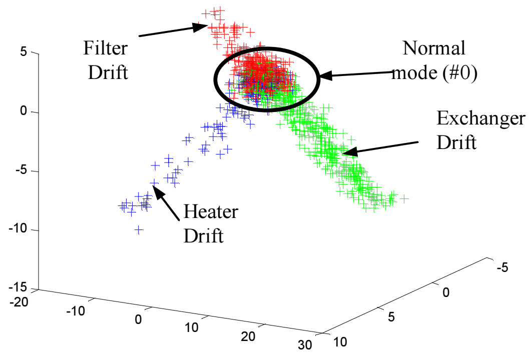

Fig. 2. : The different drifts

The supervision of the WCTC is carried out on-line according to figure 1. The AUDyC neural network learns the functioning mode of the WCTC (modelling module). In the monitoring module, the two detection tools are used in parallel to analyze the temporal outputs of the AUDyC and then detect failures and/or abnormal deviations.

Fouling is simulated by using some supplementary valves installed in the closed loop of the WCTC upstream of each component. Other failures are electrical.

Figure 3 (2D projection) illustrates a fast drift detection due to a electrical heater plugging. Figure 4 illustrates the detection of a slow drift due to the exchanger fouling.

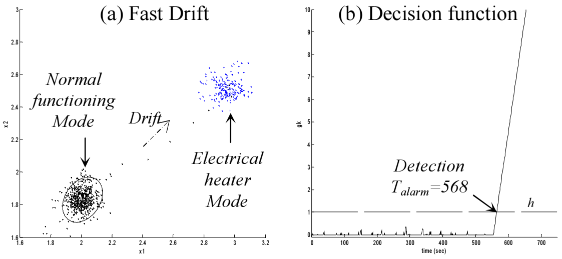

Fig. 3. : Illustrations of the fast drift detection tool

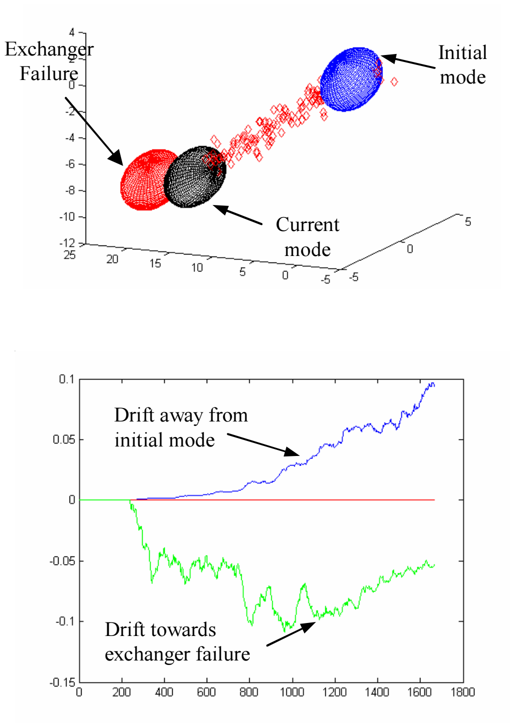

Fig. 4. : Illustrations of the slow drift detection tool

5. Conclusion

A global strategy for the monitoring of a WCTC has been presented. This one uses a specific supervision system based on a modelling module allowing the definition of updated functioning modes and specific monitoring tools designed to detect fast drifts (breakdowns) and slow drifts (fouling). Combining their properties, the monitoring of complex system such as a WCTC is reliable.

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