An Integrated Intelligent Model based Fuzzy TS NARX for Process State Detection and Prediction

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Abstract

Abstract – This research work focuses on the integrated intelligent model development for process state (especially for fault) detection, behavior prediction for complex processes. In the model architecture, Fuzzy Neural Networks (FNNs) are applied as process state classifiers for process state (fault) detection; different Neural Networks (NNs) are applied for system identification of process characteristics in different process states. The model detects process states (faults) and predicts process output according to process input and historical output (behaviors), whose combination of influences generates the final results of process state (fault) detection and quantitative prediction. The whole model is constructed based on Fuzzy TS dynamic Nonlinear AutoRegressive with eXogenous input models (NARX models). Furthermore, model optimization is investigated for model adaptability.

The study and application results for supply forecasting indicate that the model not only has good performance for process state (fault) detection, but also provides quantitative prediction of process output. It can be applied in process state identification, fault detection, diagnosis and prediction for process behavior, etc.

I. INTRODUCTION

An industrial process is a series of operations performed in manufacturing or some other activities. Monitoring and diagnosis are particularly important in aligning the process with other processes and ensuring that the process operates according to the desired specifications [1]. Various methods have been applied in monitoring and diagnosis in real processes or systems, for example, the methods based on system dynamic physical model, parameter estimation method, system identification, signal process and analysis, probability and statistic methods, Bayesian classifier and inference method and so on. These methods might work well under the circumstance of simple plants with relatively simple working environment and operation range. However, due to more and more complex and flexible industrial processes, further requirements from industrial applications are to cover [5] [7] [9]:

- Further data analysis, behavior prediction and decision support for diagnosis system.
- Well working in some dynamic, wide range operations and complex processes.
- Dealing with complex and uncertain processes without more priori process information; treating with some important variables, which are uncertain, or not numerical.
- Not only monitoring, but also more diagnosis, prediction and control.

- Providing making decision support for the relationship between symptom and fault, etc...

All these needs provide big challenges to monitoring and diagnose systems [5]. In this paper, general system model is first introduced for fundamental model for process description. And then, based on those model structures, a new integrated model with intelligence technologies are suggested to fulfill the requirements from above.

II. GENERAL SYSTEM MODEL

2.1 Process Dynamical Model

As the nomenclature of nonlinear dynamical model is based on the terminology used to categorize linear input-output models, it can be summarized by the general family [8]:

\[ A(q) y(k) = \frac{B(q)}{F(q)} u(k) + \frac{C(q)}{D(q)} e(k) \] (1)

where, \(q\) denotes the shift operator. For instance, \(A(q)\) is a polynomial in \(q-1\). This model can be given in a "pseudo-linear" regression form (2) [8]:

\[ \hat{y} = Q^T X(k) \] (2)

where the regressors, i.e., the components of \(X(k)\) can be given by: 1) \(u(k-i), i=1,...,n_u\), control signals (associated with the B polynomial); 2) \(y(k-i), i=1,...,n_y\), measured process outputs (associated with the A polynomial); 3) \(\hat{y}(k-i)\) simulated outputs from the past \(u(k)\) (associated with the F polynomial); 4) \(u(k-i)\rightarrow\hat{y}(k-i)\rightarrow\hat{y}(k-i)\), prediction errors (associated with the C polynomial); 5) \(e_i = y(k-i) - \hat{y}(k-i)\) simulation errors (associated with the D polynomial).

Based on these regressors, different types of model structures can be constructed. For instance, the simplest linear dynamical model is the finite impulse response (FIR) model, some special cases of (1) as the Box-Jenkins (BJ) model (A=1), the ARMAX model (F=D=1), the output-error (OE) model (A=C=D=1) and the ARX model (F=C=D=1)[8].

Following this nomenclature of linear models, it is natural to construct similar nonlinear model as: \(NFIR, NOE, NARX, NARMAX\) and \(NBI\), etc. The \(NARX\) model is called a series parallel model, and the
NARMAX, NOE and NBJ models are recurrent models, because they use the estimated output that constitutes a feedback. Usually, the NARX model is frequently used for system description and identification [2], whose regressors are used as follows in equation 3 [8]:

\[ X(k) = [y(k-1), ..., y(k-n_y), u(k-1), ..., u(k-n_u)] \]

(3)

It means, the prediction output of NARX model just relies on real system input and output from past.

2.2 Fuzzy Takagi-Sugeno-Kang Inference Model

Fuzzy inference is the process of formulating the mapping from a given input to an output using fuzzy logic. The mapping then provides a basis form which decisions can be made, or patterns discerned [3]. Fuzzy inference systems have been successfully applied in several fields such as automatic control, data classification, decision analysis, expert system, system modeling and identification and so on. Typically, there are two main types of fuzzy inference system in the fuzzy logic: Mamdani- and Sugeno type [2][3].

The Takagi-Sugeno-Kang (TSK or TS) method introduced in 1985 [3], differs from Mamdani mainly in the fact that the TS output membership functions are either linear or constant [4]. A type rule in a TS fuzzy model has the form:

If Input1=x, and Input2=y then output is Z=ax+by+c .

How the TS rule operates is shown in the following diagram

In the figure, \( F_1(x) \) and \( F_2(x) \) are the membership functions for input1 and input2, the final output of the system is the weighted average computed in equation 4.

\[ Y = \sum_{i=1}^{V} w_i z_i \]

(4)

Some more advantages of the TS model are: 1) It is computationally efficient; 2) It works well with linear techniques; 3) It works well with optimization and adaptive techniques; 4) It is guaranteed continuity of the output surface; 5) It is well-suited to mathematical analysis [4].

2.3 Fuzzy TS Models of Dynamic Systems

The dynamic system is usually based on Nonlinear AutoRegressive with eXogenous input (NARX) model structure. The NARX model establishes a nonlinear relation between system outputs and inputs. The system prediction output is a combination of system output produced by real inputs and system output produced by historical output behavior. It can be expressed as formula (5):

\[ y(k) = f(y(k-1), ..., y(k-n_y), u(k-1), ..., u(k-n_u)) \]

(5)

Here, \( n_y \) and \( n_u \) are the maximum lags considered for the output, and input terms, respectively, and \( f \) represents the mapping of fuzzy model.

The fuzzy TS NARX model interpolates between local linear, time-invariant (LTI) ARX models as follows: \( R_j \) if \( Z_i(k) = A_1 j \) and \( ... \) and \( Z_i(k) = A_n j \) Then

\[ y(k) = \sum_{j=1}^{n_y} a_j y(k-i) + \sum_{i=1}^{n_u} b_i u(k-i - n_u) + c \]

(6)

where the elements of \( Z(k) \) "scheduling vector" are usually a subset of the \( x(k) \) regressors. \( Z(k) \) contains the variables relevant to the nonlinear behavior of the system [8],

\[ Z(k) = [y(k-1), y(k-n_y), u(k-1), u(k-n_u), u(k-n_u-n_y)] \]

while the \( f_j(q(k)) \) as consequence functions contain all the regressors \( q(k) = [x(k-1)] \),

\[ f_j(q(k)) = \sum_{i=1}^{n_y} a_j y(k-i) + \sum_{i=1}^{n_u} b_i u(k-i - n_u) + c \]

(7)

In the next section, the fuzzy TS NARX model is developed and applied for process state identification (fault detection) and output predication of processes.

III. INTEGRATED INTELLIGENT MODEL BASED ON FUZZY NARX TS MODEL

3.1 Integrated Intelligent Model objectives

The main task of the model is to detect the process state (fault) and quantitatively predict process output so as to implement process diagnosis and control. Therefore, it consists of three parts as follows [5]:

- Process state (fault) detection: Detecting if an abnormal state or fault occurs.
- Fault identification: Quantitatively identifying process state (fault), namely, the process state (fault) amplitudes.
- Decision-making: Finding the decision rule for fault occurrence and accompanying phenomena.

Here, the work focuses on:

a. Residual signal generator based on fuzzy classification: Due to not explicitly available discrimination border, a fuzzy classifier is needed to distinguish between normal and abnormal (fault) state in real processes. When a process works on a certain operation point, the performance of the process fluctuates in a certain range. When an abnormal state (fault) occurs, the process performance or work status could make corresponding response and change. Hence, the process state fluctuates beyond initial range
and these process states can be divided into at least two
different states: abnormal and normal ones. This is illustrated
in figure 2 by simple description. Process state (fault) detection is then implemented by classifying these normal or
abnormal states. Because process state definition cannot be
done explicitly, fuzzy information is applied and a classifier
based fuzzy information process is introduced as residual
signal generator.

Figure 2: The possible partition of process state in industrial process.

b. Process state (fault) identification and process predication based on fuzzy information and inference: The result of process state (fault) classification includes a fuzzy
degree of different process state (fault) occurrence, and hence,
it was natural to involve this fuzzy information for process output prediction so as to improve the accuracy.

c. Knowledge and rule extraction for making decision: Process states and their corresponding data are used to
generate decision rules supported by some data mining
technologies.

3.2 Outline of the Architecture

The outline of an integrated intelligent model is shown in
figure 3.

Figure 3: The Architecture of the Integrated Intelligent Model

The model is built based on black-box principles by learning
and training from history data without understanding priori
laws inside of real system. In training phase: 1) the input-output data is fuzzyfied and
different process states are defined and described with
membership functions; 2) a state classifier based Fuzzy Neural
Networks (FNNs) is trained as fault signal residual generator
by these fuzzyfied input-output data; 3) Based on the different
process states and data, the fault diagnosis or prediction model
is established by system identification with NNS; 4) Some
decision rules between fault symptoms and fault can be mined
from input data in different process states and corresponding process states.

In work phase: When new input data is coming, state
classifier first identify what process state occurs
(normal or fault state), the output of FNNs is also
fuzzy information, which is used in expressing the
different process state (fault state) with this fuzzy
degree and also regarded as fuzzy residual signal for
fault detection. Then the corresponding sub units are
called for quantitatively predicting process output
based on certain fuzzy TS inference models. The whole model output is determined by a fuzzy residual
signal and fault threshold in the Fuzzy TS NARX model. In addition, a model optimization scheme for
adaptive fault threshold is developed for time-
depending model adaptability.

3.3 Mathematic model of the work unit

The work unit in figure 3, which is used to detect
process state (fault) and to predict process output here,
can be explained as a fuzzy TS NARX model, which is
shown in figure 4.

Figure 4: The Fuzzy TS Dynamic model for process state detection
and process predication

There, the input1 represents all process input variables
and the input2 represents all process output from the past. Unit 1 and unit 3 represent fuzzyfication of
input1 and input2 respectively, unit 2 and unit 4 represent fuzzy state classifier for input1 and input2 respectively, and unit 5 represents fuzzy operation for
output result of two fuzzy state classifiers. Input1 MF,
input2 MF and Output MF represent membership function for input1, input2 and process output
variables, respectively. F1(X) and F2(X) are fuzzy
inference model function corresponding to input1 and
input2 respectively, they are identified and established
by NNS unit. The model indicates the detection of fault
and prediction of process output mainly in terms of
two important aspects: Process input variables and
real historical output data (behaviors). The final
detection result for process state (fault) is generated by
the combination of influences from real system input
and process historical behaviors. The whole process
model can be described as a NARX TS fuzzy Dynamic
model as equation 8.
If input1 (k) is $A_{ij}$ and input2(k) is $A_{j}$, then

$$y(k) = \sum_{i=1}^{n} a_{i} y(k-i) + \sum_{j=1}^{b} b_{j} u(k-i-n_{d}) + c$$

(8)

Here,

- input1(k) is a state variable produced by real system inputs; $A_{ij}$ are fuzzy sets of process states defined by the membership functions.
- input2(k) is a state variable produced by process historical output; $A_{j}$ are fuzzy sets of process state defined by the membership functions.

Under these circumstances, the fuzzy rule can be deduced from high-level description of the process as follows:

**To input 1 (for simplicity reasons, we only consider one input variable):**

1. Rule 1: If input1 leads the process into abnormal (fault) state, then the whole process is in abnormal (fault) state, where the output is set to $Z_{11}$.
2. Rule 2: If input1 leads the process into normal state, then the whole process is in normal state, where the output is set to $Z_{12}$.

**To input 2 (only consider one input variable):**

1. Rule 1: If input2 leads the process into abnormal (fault) state, then the whole process is in abnormal (fault) state, and the output is set to $Z_{21}$.
2. Rule 2: If input2 leads the process into normal state, then the whole process is in normal state, the output is set to $Z_{22}$.

The system output for response of for example input1 is given as equation 9:

$$Y_{out} = \sum_{i=1}^{a} w_{i} x_{1} + \sum_{i=1}^{w_{n}} w_{n} x_{n}$$

(9)

Here, $W_{i} \in [0, 1]$ is fuzzy degree for different process states. It is produced by state classifiers based on FNNs model. The output variable input2 is following the same principle as for input1. The whole inference rules, model and system output are illustrated in figure 5.

The functions $Z_{1i}$, $Z_{2i}$ are determined by system identification method with NNs models according to different process states and their process input variables. The final output is given as:

$$Y_{out} = a \times Y_{input} + b \times Y_{input2} + c$$

(10)

where $a$ and $b$ can be decided in terms of the influence degree of input1 and input2 to process output. If input1 and input2 play the same role to affect the real processes, then use $a=b=0.5$.

According to the system structure, the whole integrated intelligent model for process state (fault) detection and identification can now be described as:

**Fault Residual Signal Generator:** The final process state (fault) residual signal $w$ is generated by output of two fuzzy classifiers: One is used for process (fault) detection produced by real system inputs and another by historical behaviors. The outputs ($w_{1}$ and $w_{2}$) of these two fuzzy classifiers are combined by fuzzy operation to produce fault residual signal.

**Process prediction:** The final process output $Y$ is determined by the combination of two aspects: One is produced from process response by real system input, another by process historical behaviors. The final model output is calculated by the Fuzzy TS NARX model.

**Inference Rule:** In the model, the Antecedent part, which is generated by two fuzzy classifiers, gives the fault residual generator for fault detection. The Consequent part, which is generated by system identification based module NNs structure and fuzzy information, provides the predication output. These inference rules describe the relationship between process state (fault) occurrence and quantitative value of process output.

3.4 The adaptive ability

The model should be adaptive due to the uncertain, nonlinear and time-variant characteristics of real plants. Based on model structure, an optimization scheme is developed for adaptability as figure 6.

3.4.1 Optimization modeling

In the figure, some free parameters of model can be optimized so that the model output can track or match real process output as much as possible. As optimization objective function, we use:

$$F(x, \theta) = \frac{1}{N} \sum_{i=1}^{N} (f(x_{i}) - f_{w}(x_{i}, \theta))^{2}$$

(11)
which describes the Euclidean norm of the error between prediction output vector of model and real output vector of plant [2].

The parameter $\delta$ is the threshold, which is used for indicating fault and normal state in membership function of process state variables as illustrated in figure 7.

![Image of membership functions](image)

Figure 7: The membership functions of output and parameter $\delta$ for fault residual threshold.

The parameter $\delta$ is regarded as a threshold for fault residual signal for process state (fault) detection. When the fuzzy degree of normal process state $w_{normal} > \delta$, it indicates the process is in normal state completely, hence, the model output value is just determined by the normal state unit. When the fuzzy degree of fault state $w_{abnormal} = \delta$, the process is in abnormal (or fault) state and model output is determined by fuzzy TS model, as shown in equations 9 and 10. Hence, adjusting the parameter $\delta$ can produce different model output and process state (fault) detection. The value of $\delta$ directly affects the result of process state (fault) detection as well as the result of prediction output. Hence, the optimization scheme is:

$$\text{Find } \delta(0<\delta<1) \text{ so that } \min \left\{ \sum_{i} \left( f_i(x) - f_i(x, \delta^2) \right)^2 \right\}$$

Here, $T$ is the certain time period to consider.

IV. APPLICATION IN SUPPLY CHAIN SYSTEMS

4.1 The problem definition

One of the major challenges facing any business is how much to charge for its products and services with market change. In production and supply chain processes, it is difficult to measure, diagnose, predict and control whole processes. Norsk Kjøttesamvirke AS is a major enterprise in the Norwegian distribution market. Its main business is to collect different kinds of goods from many different companies and then to sell, supply and distribute them to different store markets in Norway. The company wishes to increase prediction ability and flexibility to organize and plan their production, sales, store and transport, etc., what will further help them to decide the price and amount for the market. The aim of the project is to develop a supply-forecasting model and business analysis model for making decision according to historical data. All relevant data of product supply have been received from SINTEF Industrial Management in Norway. The data sets contain a list of the customers and their goods order every day every year.

The supply chain process is complex, nonlinear and time-varying process, hence, the good way is to model the process from historical data according to black-box principles. Analyzing the data distribution, we can conclude that it is easy to predict goods supply in normal state but difficult to do it under some abnormal state circumstances, for example, abrupt increase or decrease from customer orders, etc. In essence, from technical point of view, this kind of problems can be explained as process state (normal or abnormal state) detection and process predication problem, which is described as follows:

- The function of process state (fault) detection can be applied to find and detect the aberrance state in supply chain process and.
- The function of process output prediction can be used for analysis and prediction of the supply chain process.

Hence, the integrated intelligent model based on fuzzy TS NARX in this paper can be applied to solve this business problem.

4.2 The application results

The integrated intelligent model is applied in the supply chain process for abrupt change detection and product supply forecasting, the prediction result for one kind of goods is given in table 1. The comparison between real data and prediction value is shown in figure 8.

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In table 1, error (IA is the relative error and error (DR is absolute error. From the figure 9, it is easy to see the integrated intelligent model has good forecasting ability, especially in prediction of abrupt state changes in the supply chain process.

The above prediction value is obtained when fault residual threshold value $\delta$ is optimized to minimize the error between model and real plant; the error curve is illustrated when $\delta$ from 0 to 1 as figure 9.

In this paper, the integrated intelligent model based on Fuzzy TS NARX model is developed for process state (fault) detection and prediction of process behavior. In the Fuzzy TS dynamic NARX model, the Antecedent part, which is generated by two fuzzy classifiers, constructs the residual generator for process state (fault) detection and the Consequent part, which is generated by system identification based module Neural Networks structures and fuzzy partition information, constructs the process output predication. These inference rules based on fuzzy TS model describe the relationship between process state (fault occurrence) and its quantitative process output. The model adaptability is implemented by model optimization scheme for adaptive residual signal generation.

V. CONCLUSIONS

References


