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 (especial 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]:

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

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].

$$\hat{y} = Q^T X(k) \tag{2}$$

where the regressors, i.e., the components of $X(k)$ can be given by: 1) $u(k-i)$, $i=1,\dots n_b$, control signals (associated with the B polynomial); 2) $y(k-i)$, $i=1,\dots n_a$, 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) $e(k-i)=\hat{y}(k-i)-y(k-i)$, prediction errors (associated with the C polynomial); 5) $e_u = y(k-i) - y_u(\hat{k}-i)$ 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]:

$$X(k)=[y(k-1),\dots,y(k-n_a),u(k-1),\dots,u(k-n_b)] \qquad (3)$$

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

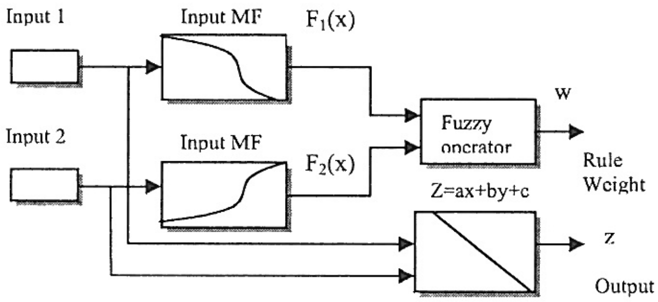

Figure 1: The Fuzzy TS Fuzzy inference model.

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

$$Y = \sum_{i=1}^{N} w_i z_i \Big/ \sum_{i=1}^{N} w_i \qquad (4)$$

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):

$$\hat{y}(k)=f(y(k-1),\dots y(k-n_a),u(k-n_d),\dots u(k-n_b-n_d)) \qquad (5)$$

Here, n_a and n_b 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:

Rj: If $Z_1(k)$ is A1,j And …And $Z_n(k)$ is An,j

Then

$$\hat{y}(k)=\sum_{i=1}^{n_a} a_i^j y(k-i)+\sum_{i=1}^{n_b} b_i^j u(k-i-n_d)+c^j\,, \qquad (6)$$

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],

$$Z(k)\in\{y(k-1),\dots y(k-n_a),u(k-n_d),\dots u(k-n_b-n_d)\}$$

while the $f_j(q(k))$ as consequence functions contain all the regressors q(k)=[X(k) 1],

$$f_j(q(k))=\sum_{i=1}^{n_a} a_i^j y(k-i)+\sum_{i=1}^{n_b} b_i^j u(k-i-n_d)+c^j \qquad (7)$$

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.

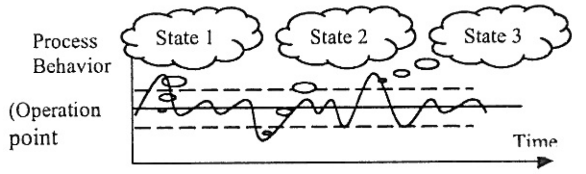

Figure 2: The possible partition of process state in industrial process.

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.

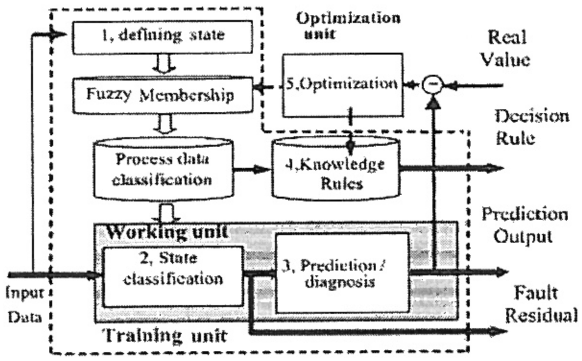

Figure 3: The Architecture of the Integrated Intelligent Model

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.

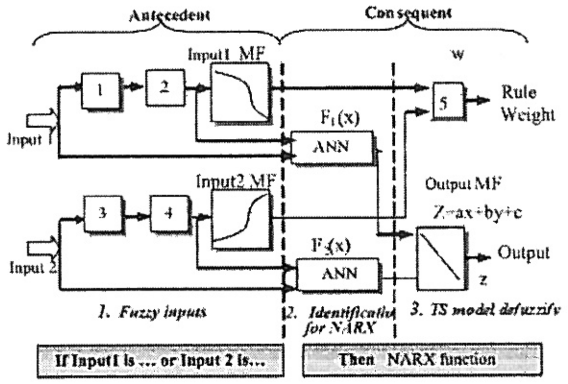

Figure 4: The Fuzzy TS Dynamic model for process state detection and process prediction

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. $F_1(X)$ and $F_2(x)$ 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.

Rj: If input1 (k) is $A_{1,j}$ And input2(k) is A_{2j}

Then

$$\hat{y}(k)=\sum_{i=1}^{n_a} a_i^j y(k-i)+\sum_{i=1}^{n_b} b_i^j u(k-i-n_d)+c^j \quad (8)$$

Here,

- *input1(k)* is a state variable produced by real system inputs; $A_{1,j}$ are fuzzy sets of process states defined by the membership functions.
- *Input2(k)* is a state variable produced by process historical output; $A_{2,j}$ 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):

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}.*

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):

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}.*

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:

$$Y_{input1}=\frac{\sum_{i=1}^{N} w_{1i}z_{1i}}{\sum_{i=1}^{N} w_{1i}}=\sum_{i=1}^{N} w_{1i}z_{1i} \quad (9)$$

Here, $w_i \in [0, 1]$ is fuzzy degree for different process states. It is produced by state classifiers based FNNs model. The output to variable Input2 is following the same principle as for input1. The whole inference rules, model and system output are illustrated in figure 5.

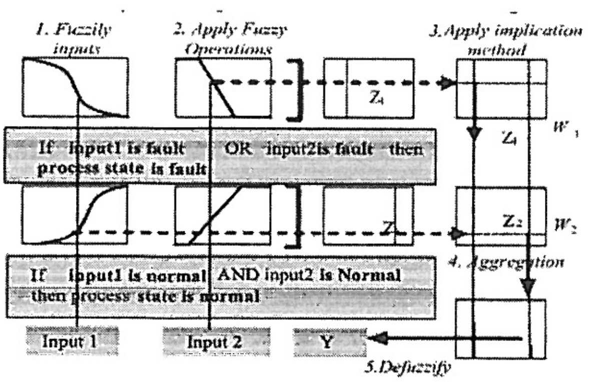

Figure 5: The fuzzy TS NARX model, rule and model output.

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:

$$Y_{total}=a\times Y_{input1}+b\times Y_{input2}+c \quad (10)$$

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 predication: 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 NAXR 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 [2][10].

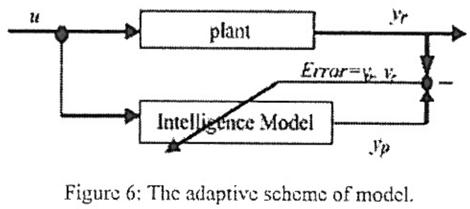

Figure 6: The adaptive scheme of model.

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:

$$F(x,\vartheta)=\sqrt{\sum_{t}^{T}(f(x_t)-f_a(x_t,\vartheta)^2)} \quad (11)$$

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

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

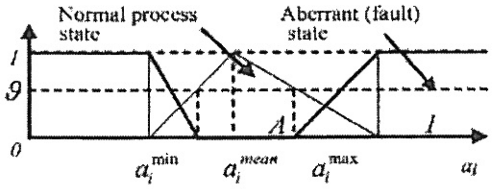

Figure 7: The membership functions of output and parameter ϑ for fault residual threshold.

The parameter ϑ is regarded as a threshold for fault residual signal for process state (fault) detection. When the fuzzy degree of normal process state $w_{normal} > \vartheta$, 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 $w_{abnormal} > \vartheta$, 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 ϑ can produce different model output and process state (fault) detection. The value of ϑ directly affects the result of process state (fault) detection as well as the result of prediction output. Hence, the optimization scheme is:

$$\textit{Find } \vartheta(0<\vartheta<1) \text{ so that } \min\left\{\sqrt{\sum_{t}^{T}(f(x_i)-f_a(x_i,\vartheta)^2)}\right\}$$

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 Kjøttsamvirke 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 sale, 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.

Table 1: The real data, prediction result and prediction error

(Training data: from 36th week 1999 to 30th week 2000, Test data: from 30th week 2000 to 36th week 2000)

Date	Real Data	Prediction data	Error(I)A	Error(I)R
1	3845.6	3978.508908	132.9089082	0.03456129
2	853.6	1263.155022	409.5550217	0.47979735
3	3571.2	3673.220308	102.020308	0.02856751
4	2621.6	3947.710762	1326.110762	0.50584024
5	3258.4	2394.627931	863.772069	0.26509086
6	4014.4	3729.258218	285.1417825	0.07102974
7	828	1199.454714	371.4547143	0.4486168
8	2791.2	3265.11908	473.9190804	0.16979044
9	2595.2	2896.134694	300.9346937	0.11595819
10	3332	2409.66559	922.3344104	0.27681105
11	4426.4	5238.65	812.25	0.18350127
12	764	1135.905688	371.9056879	0.48678755
13	3001.6	3072.233135	70.6331349	0.02353183
14	1364	1436.226056	72.22605588	0.05295165
15	4681.6	5210.03	528.43	0.1128738
16	4365.6	5381.76	1016.16	0.23276526
17	1477.6	1151.826798	325.7732022	0.22047455
18	3612.8	2598.545425	1014.254575	0.2807392
19	1976	2364.309353	388.3093532	0.19651283
20	3333.6	2502.610542	830.9894581	0.2492769
21	3695.2	3921.660722	226.4607215	0.06128511
22	1202.4	1295.269537	92.8695372	0.07723681

23	2339.2	3197.580795	858.3807949	0.36695485
24	2385.6	2530.879489	145.2794887	0.06089851
25	2948	2425.506428	522.4935717	0.17723663
26	3248	3044.183005	203.816995	0.06275154
27	782.4	1194.350247	411.9502465	0.52652128
28	2315.2	2942.125134	626.9251342	0.2707866
29	2260.8	2915.480609	654.6806093	0.28957918
30	1560.8	1489.84179	70.95821019	0.04546272
31	782.4	1117.693583	335.2935829	0.42854497
Average Error value			476.3932939	0.21944311

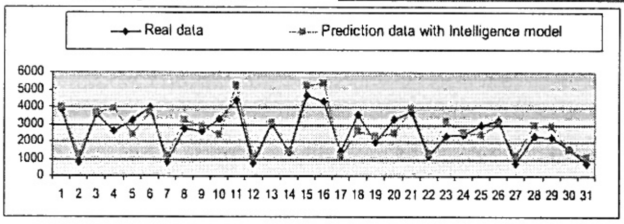

Figure 9: The comparison between prediction result and real data (When $\mathcal{G}$=0.95)

In table 1, error (I)A is the relative error and error (I)R 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 $\mathcal{G}$ is optimized to minimize the error between model and real plant; the error curve is illustrated when $\mathcal{G}$ from 0 to 1 as figure 9.

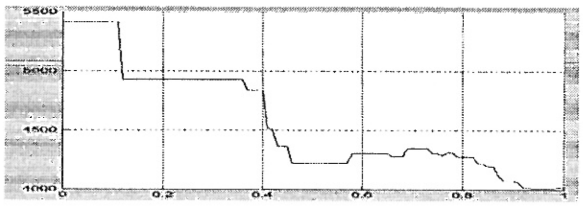

Figure 9: The square error curve with respect to $\mathcal{G}$

When $\mathcal{G}$=0.95, then model has minimum error with real process during the certain time period (T=31).

V. CONCLUSIONS

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.

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