

# NEURO-FUZZY BASED FAULT DIAGNOSIS APPLIED TO AN ELECTRO-PNEUMATIC VALVE

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**Abstract:** The early detection of faults (just beginning and still developing) can help avoid system shutdown, breakdown and even catastrophes involving human fatalities and material damage. Computational intelligence techniques are being investigated as extension of the traditional fault diagnosis methods. This paper discusses the properties of the TSK/Mamdani approaches and neuro-fuzzy (NF) fault diagnosis within an application study of an electro-pneumatic valve actuator in a sugar factory. The key issues of finding a suitable structure for detecting and isolating ten realistic actuator faults are described.  
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**Keywords:** Neuro-fuzzy networks, Fault Diagnosis, Fault Isolation, Fuzzy Hybrid Systems, Actuators

## 1. INTRODUCTION

The mathematical model used in the traditional Fault Detection and Isolation (FDI) methods is sensitive to modelling errors, parameter variation, noise and disturbance. Process modelling has limitations, especially when the system is complex and uncertain and the data are ambiguous i.e. not information rich.

Computational Intelligence (CI) methods (Neural Networks (NN), Fuzzy Logic (FL), Evolutionary Algorithms (EA) are known to overcome some of the above mentioned problems (Patton *et al* 2000). Neural networks are known to approximate any non-linear function, given suitable weighting factors and architecture. Moreover, on-line training makes it possible to change the FDI system easily in cases where changes are made in the physical process or the control system. NN can generalise when presented with inputs not appearing in the training data and make intelligent decisions in cases of noisy or corrupted data. However, the NN operates as a "black box" with no qualitative information available of the model it represents (Patton, 1994).

Fuzzy logic systems on the other hand have the ability to model a non-linear system and to express it in the form of linguistic rules making it more transparent i.e easier to interpret. They also have inherent abilities to deal with imprecise or noisy data therefore making them suitable for fault diagnosis (Dexter, 1995). Neuro-fuzzy (NF) model is a combination of neural network and fuzzy logic to exploit the learning ability of NN and the reasoning ability of FL.

This paper provides a tutorial study of the use of NF structure identification and clustering methods with application to a non-linear model of an electro-pneumatic valve system. It is well known that for the non-linear systems the problem of discriminating between uncertain model behaviour and faults present a significant challenge. This paper describes a multiple-model strategy, taking care of multiple operating points through the NF modelling framework. Section 2 outlines the value of the NF approach to modelling, whilst Section 3 enters more into details of structure identification prior to describing the NF model construction strategy in

Section 4. The remainder of the paper is concerned with the fault diagnosis application problem.

## 2. WHAT IS A NEURO-FUZZY MODEL

The Neuro-fuzzy model combines, in a single framework, both numerical and symbolic knowledge about the process. Automatic linguistic rule extraction is a useful aspect of NF especially when little or no prior knowledge about the process is available (Brown and Harris, 1994; Jang, 1995). For example, a NF model of a non-linear dynamical system can be identified from the empirical data. This model can give us some insight about the non-linearity and dynamical properties of the system.

The most common NF systems are based on two types of fuzzy models TSK (Takagi and Sugeno, 1985; Sugeno and Kang, 1988) and Mamdani (1995, 1996) combined with NN learning algorithms. TSK models use local linear models in the consequents, which are easier to interpret and can be used for control and fault diagnosis (Füssel, *et al* 1997; Ballé *et al* 1997). Mamdani models use fuzzy sets as consequents and therefore give a more qualitative description. Many neuro-fuzzy structures have been successfully applied to a wide range of applications from industrial processes to financial systems, because of the ease of rule base design, linguistic modelling, application to complex and uncertain systems, inherent non-linear nature, learning abilities, parallel processing and fault-tolerance abilities. However, successful implementation depends heavily on prior knowledge of the system and the empirical data (Ayoubi, 1995).

Neuro-fuzzy networks by intrinsic nature can handle limited number of inputs. When the system to be identified is complex and has large number of inputs, the fuzzy rule base becomes large.

NF models usually identified from empirical data are not very transparent. Transparency accounts a more meaningful description of the process i.e less rules with appropriate membership functions. In ANFIS (Jang, 1993, 1995) a fixed structure with grid partition is used. Antecedent and consequent parameters are identified by a combination of least squares estimate and gradient based method, called hybrid learning rule. This method is fast and easy to implement for low dimension input spaces. It is more prone to lose the transparency and the local model accuracy because of the use of *error back-propagation* that is a global and not locally non-linear optimisation procedure. One possible method to overcome this problem can be to find the antecedents & rules separately e.g. clustering and constrain the antecedents, and then apply optimisation.

Hierarchical NF networks can be used to overcome the dimensionality problem by decomposing the system into a series of MISO and/or SISO systems called hierarchical systems (Tachibana and Furuhashi, 1994). The local rules use subsets of input spaces and are activated by higher level rules.

The criteria on which to build a NF model are based on the requirements for faults diagnosis and the system characteristics. The function of the NF model in the FDI scheme is also important i.e. Pre-processing data, Identification (Residual generation) or classification (Decision Making/Fault Isolation). For example a NF model with high approximation capability and disturbance rejection is needed for identification so that the residuals are more accurate. Whereas in the classification stage, a NF network with more transparency is required.

The following characteristics of NF models are important:

- Approximation/Generalisation capabilities
- Transparency: Reasoning/use of prior knowledge /rules
- Training Speed/ Processing speed
- Complexity
- Transformability: To be able to convert in other forms of NF models in order to provide different levels of transparency and approximation power.
- Adaptive learning

Two most important characteristics are the generalising and reasoning capabilities. Depending on the application requirement, usually a compromise is made between the above two.

## 3. STRUCTURE IDENTIFICATION OF NF MODELS

For complexity reduction and transparency, *Structure Identification* methods can be applied to find appropriate input partition, rules & membership functions (MFs). Methods like Evolutionary Algorithms (EA), Classification and Regression Trees CART (Jang, 1994), Clustering and unsupervised NN (e.g. like the Kohonen feature maps) can be used. Once the structure is determined i.e. the rules and input membership functions, the consequent parameters can be identified by optimisation techniques like *Least-Squares Estimation*. The Product Space Clustering approach can be used (Babuska, 1998) for structure identification of TSK & Mamdani fuzzy models. For a MISO non-linear dynamic system with  $p$  inputs, the Product space  $(X \times Y) \subset \mathfrak{R}^{p+1}$  is divided in subspaces in which linear models can approximate the non-linear system. Locally linear model tree LOLOMOT algorithm developed by Nelles can be used to identify a TSK fuzzy model with dynamic linear models as consequents. When using such structure identification techniques, a major issue is the sensitivity to uneven distribution of data. For example in most clustering algorithms, more clusters are created in regions with more data. A possible solution to this is problem may be to initialise the algorithm with large number of clusters.

Transparency of the NF models can be enhanced by tuning rules & MFs (Babuska, 1998). This kind of methods are referred to as *structure simplification/optimisation techniques*. To find the optimal

number of rules, different cluster validity measures and methods like Compatible Cluster Merging CCM (Krishnapuram and Freg, 1992) can be used. At NF model level the rules are further simplified by merging similar fuzzy sets & removing fuzzy sets similar to the universal set. Setnes *et al.*, (Setnes and Kaymak 1998) used a supervised fuzzy clustering algorithm that uses input-output data, orthogonal techniques and tuning for complexity reduction.

#### 4. CONSTRUCTION OF NEURO-FUZZY MODELS

Two major classes of knowledge representation in fuzzy modelling are proposed by Takagi and Sugeno (Takagi and Sugeno, 1985) and Mamdani (Mamdani *et al* 1976).

In linguistic or Mamdani fuzzy model both antecedents and consequents are linguistic fuzzy sets. This model is mainly used to give a more linguistic description of the process

This fuzzy model can be represented as a multi-layer NF network (Fig.1) in which the input/output membership functions, rules, *normalisation* and *de-fuzzification* stages are expressed as neuron layers.

The  $i_{th}$  input fuzzy set in Layer-1 can be described by a Gaussian membership function with centres  $m_i$  and spread  $\sigma_i$ .

$$\mu_{A_i}(x) = \exp\left[-\left\{\frac{(x-m_i)^2}{\sigma_i}\right\}\right] \quad (1)$$

The second layer consists of rule neurons. The firing strength of each rule is given by:

$$\alpha = \min([\mu_{A_1}(x), \mu_{A_n}(x), \dots, \mu_{A_n}(x)]) \quad (2)$$

or

$$\alpha = \prod \mu_{A_i}(x) \quad (3)$$

Applying COA de-fuzzification (Layers-3,4,5) the output  $y$  can be calculated as (W Hauptmann and K Heesche 1995)

$$y = \frac{\sum_k M_k \cdot \sum_j (w_{kj} \cdot \alpha_j)}{\sum_k A_k \cdot \sum_j (w_{kj} \cdot \alpha_j)} \quad (4)$$

where  $M_k$  and  $A_k$  are the moments and areas of the  $k_{th}$  output membership function and  $w_{kj} = 1$  if partial connection exists  
0 otherwise

The rules can be expressed as:

$$\begin{aligned} R_1: & \text{if } x_1 \text{ is } A_1 \text{ and } x_2 \text{ is } B_1 \dots \text{ then } y \text{ is } C_1 \\ R_2: & \text{if } x_1 \text{ is } A_2 \text{ and } x_2 \text{ is } B_2 \dots \text{ then } y \text{ is } C_2 \\ & \dots \\ R_n: & \text{if } x_1 \text{ is } A_n \text{ and } x_2 \text{ is } B_n \dots \text{ then } y \text{ is } C_n \end{aligned}$$

Where  $(A_1, A_2 \dots A_n, B_1, B_2 \dots B_n, \dots)$  are the input fuzzy sets and  $(C_1, C_2 \dots C_n, \dots)$  are the output fuzzy sets. The number of trainable parameters is usually large and some structure identification is needed to find the optimal network i.e. the number of rules,

shape and position of the membership functions is determined. EA or Gradient based algorithms can be used for training. This kind of network is more transparent and close to human reasoning but the complexity is high and the training is difficult.

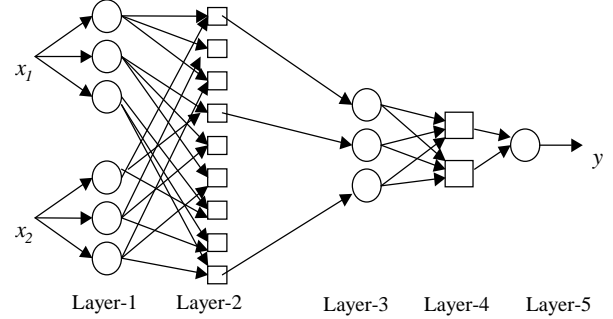


Fig. 1 Structure of Mamdani NF model.

TSK models with linear functions as consequents can be expressed as a non-linear function approximation by local linear models selected by fuzzy rules. In TSK fuzzy system (Fig. 2) the antecedents are similar to the Mamdani fuzzy system. The consequents can be any function describing the response of the model within the fuzzy region.

The same approach is applied as in the previous network, to express the TSK fuzzy system as a neural network. Fig.2 shows an example of such a network with two inputs, one output and two rules. Antecedent and consequent parameters can be optimised by Gradient-based optimisation algorithms. Hybrid learning rule by Jang (1993) can be applied for faster learning.

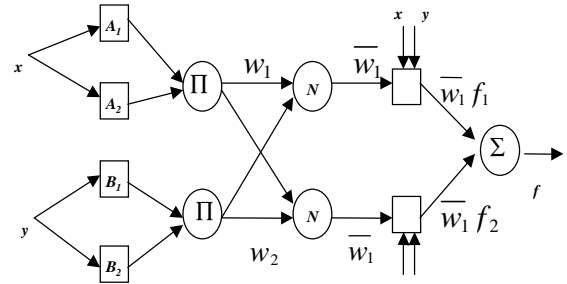


Fig. 2 Structure of TSK NF model.

The output of this model can be expressed as:

$$f = \frac{w_1 f_1 + w_2 f_2}{w_1 + w_2} = \bar{w}_1 f_1 + \bar{w}_2 f_2 \quad (5)$$

where  $f_1$  and  $f_2$  are the outputs of the two sub-models ( $f_i = a_i x + b_i y + c_i$ ;  $i=1,2$ ) and  $a_i, b_i$  and  $c_i$  are the linear parameters of  $i_{th}$  linear model. The rules are in the following form:

$$\begin{aligned} R_1: & \text{if } x \text{ is } A_1 \text{ and } y \text{ is } B_1 \text{ then } f_1 \\ R_2: & \text{if } x \text{ is } A_2 \text{ and } y \text{ is } B_2 \text{ then } f_2 \end{aligned}$$

TSK fuzzy models are suitable for the accurate modelling and identification but are less transparent than Mamdani models.

## 5. NF BASED FAULT DETECTION AND ISOLATION

Fig. 3 describes a FDI scheme in which several NF models are constructed to identify the faulty & the fault free behaviour of the system.

$$r_i(k) = f \left( \begin{matrix} u(k), u(k-1), \dots, u(k-n_u), \\ y(k), y(k-1), \dots, y(k-n_y) \end{matrix} \right); i = 1 \dots n \quad (6)$$

Each residual  $r_i$  in (6) is ideally sensitive to one particular fault in the system. In practice however because of noise and disturbances, residuals are sensitive to more than one faults.

To take into account the sensitivity of residuals to various faults and noise we apply a NF classifier. A linguistic style (Mamdani) NF network is used which processes the residuals to indicate the fault.

This NF model is constructed with following set of rules:

*If  $r_1$  is small ...  $r_r$  is large ...  $r_n$  is small  
then fault, is large*

Fuzzy threshold evaluation (7) is employed to take into account the imprecision of the residual generator at different regions in the input space.

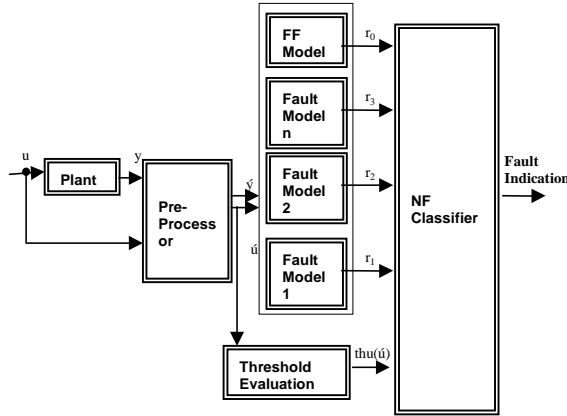


Fig. 3 Neuro-fuzzy based FDI scheme.

$$th_v(u) = \frac{\sum_{i=1}^C th_i \mu_i(u)}{\sum_{i=1}^C \mu_i(u)} \quad (7)$$

$C$  is the total number of I/P regions with different sensitivity to faults and a multidimensional fuzzy set  $\mu_i$  defines the fuzzy boundary of  $i_{th}$  such region. This approach heavily depends on the availability of the faulty and fault free data and it is more difficult to isolate faults that appear in the dynamics.

Residuals can also be generated by a non-linear dynamic model of the plant that approximates a non-linear dynamic system by local linear models. Such a model can be obtained by *Product space clustering* (Babuska 1998), or tree-like algorithms (LOLMOT algorithm by Nelles, 1995). Each local model is a

linear approximation of the process in an I/P subspace and the selection of the local model is fuzzy. The output of such model can be described by

$$y = \frac{\sum_{i=1}^C \alpha_i(u_s) \cdot f_i}{\sum_{i=1}^C \alpha_i(u_s)} \quad (8)$$

where  $f_i$  is the  $i_{th}$  local linear model given by:

$$f_i = b_{i,1}u(k) + b_{i,2}u(k-1) + \dots + b_{i,n_u}u(k-n_u) + a_{i,1}y(k) + a_{i,2}y(k-1) + \dots + a_{i,n_y}y(k-n_y) + c_i \quad (9)$$

$a_i$ ,  $b_i$  and  $c_i$  are the parameters of the  $i_{th}$  model,  $u_s$  is the I/P subspace defining the operating point,  $\alpha_i$  is the degree to which the  $i_{th}$  local model is valid at this operating point.

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From  $a_i$ ,  $b_i$  and  $c_i$  physical parameters like time constants, static gains, offsets etc (Füssel 1997) can be extracted for each operating point and can be compared with the parameters estimated online. This approach heavily depends on the accuracy of the non-linear dynamic model described above. Also the output error should be minimum when operated in parallel to the system. Moreover, this method requires that there is sufficient excitation at each operating point for online estimation of parameters.

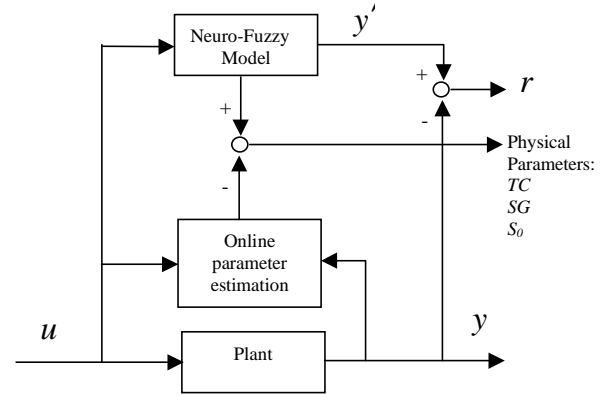


Fig. 4. TSK NF based FDI scheme.

## 6. CASE STUDY: FDI OF AN ELECTRO-PNEUMATIC VALVE ACTUATOR

The valve considered for FDI is an electro-pneumatic flow controller in the evaporation stage of a sugar factory. Here we constructed a non-linear mathematical model of the valve using SIMULINK and MATLAB. The model is then used to generate faulty/ fault-free data to evaluate the Neuro-fuzzy based fault isolation schemes presented in the

previous sections. The whole valve assembly consists of 3 main parts (Fig. 5):

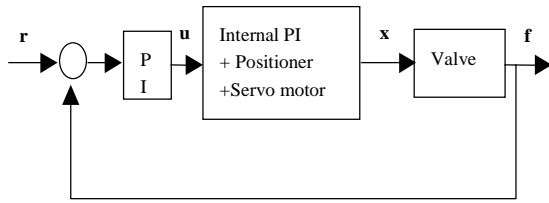


Fig. 5 Main parts of the valve assembly.

**The PI controller** controls the Positioner & Actuator output to regulate the flow through the valve

**Positioner and Actuator:** Pneumatic pressure is applied to the servomotor diaphragm to control the stem position that changes the flow. The Positioner adjusts this pressure input to the servomotor to obtain the correct stem position of the actuator.

**The Valve:** is the final element in the assembly which alters the flow according to the stem position.

The following list of faults are considered in the valve actuator assembly:

- $f_1$  - External PI controller proportional gain fault
- $f_2$  - External PI controller integral gain fault
- $f_3$  - Increased friction of the servomotor
- $f_4$  - Decreased elasticity of the servomotor
- $f_5$  - Decrease of pneumatic pressure
- $f_6$  - Internal PI controller fault
- $f_7$  - Internal position sensor fault
- $f_8$  - Valve clogging
- $f_9$  - Valve leakage
- $f_{10}$  - Chocked flow

Two neuro-fuzzy models are used here with transparent structure. A TSK structure with linear dynamic models as consequents is used to approximate the internal PI controller, the Positioner and servomotor. This system's non-linearity is mainly in the dynamics i.e. a transparent TSK model is ideal for this case. The TSK model identified has three locally linear models as consequents. The time constants of these local models are 18sec, 12sec and 8sec, respectively which show that the system is faster at high values of flow and slower at the low values.

Figure 6 shows the performance of the TSK model in closed-loop, parallel to the system.

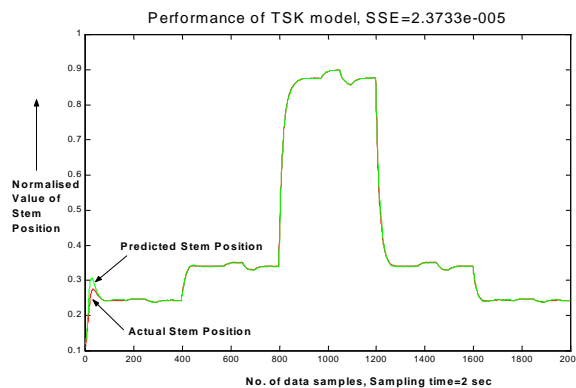


Fig. 6 Performance of TSK model.

From the local models, and *RLSE* the changes in physical parameters e.g. time constant ( $r_{TC}$ ), static gain ( $r_{SG}$ ), static ( $r_{S0}$ ) offset and settling time ( $r_{ST}$ ) are computed. These changes are the residuals which can be used for fault isolation.

A Linguistic/Mamdani NF model is identified to approximate the valve. The model input is the stem position  $x$  and the output is volumetric flow rate  $f$ . From input set-point flow and measured flow, integrating and using *RLSE*, the control input  $u$  can be predicted. GK-clustering algorithm (Gustafson & Kessel 1979) is used to partition the input space (Fig. 7), where clusters are projected onto the I/O space to find MF's. Gradient-based optimisation method is used to fine-tune the MFs (Fig. 8).

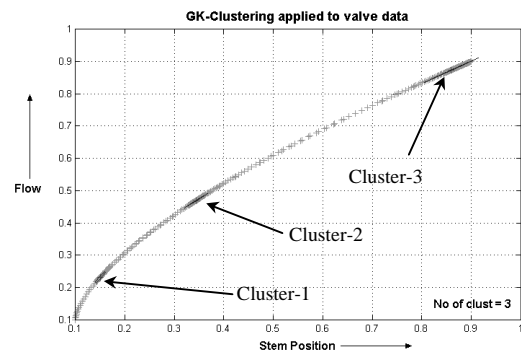


Fig. 7. Valve data clustered in three groups.

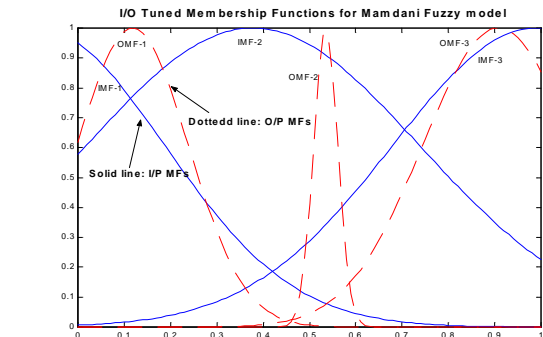


Fig. 8 Tuned I/O MFs for Mamdani model.

Table 1: Fault Isolation

	$f_1$	$f_2$	$f_3$	$f_4$	$f_5$	$f_6$	$f_7$	$f_8$	$f_9$	$f_{10}$
$r_u$	Op	Op	~	~	~	~	~	~	~	~
	+	-								
	Cl	Cl								
	-	+								
$r_x$	~	~	~	~	~	~	Ch	~	~	~
$r_f$	~	~	~	~	~	~	~	Op	Op	-
								Cl	Cl	
								-	+	
$r_{st}$	~	~	+	+	0	-	~	~	~	~
$r_{tc}$	~	~	+	-	+	-	~	~	~	~
$r_{s0}$	~	~	0	0	0	+	~	~	~	~

Op+ : Positive value when valve is being opened  
 Op- : Negative value when valve is being opened  
 Cl+ : Positive value when valve is being closed  
 Cl- : Negative value when valve is being closed  
 Ch : Changed

The predicted values  $u$ ,  $x$ ,  $f$  and the measured values are used to generate the residuals  $r_u$ ,  $r_x$ ,  $r_f$ . Fault isolation table given in table-1 shows that some faults could only be detected during the time when the valve is being opened and closed. Moreover, choked flow could only be detected at high values of flow.

## 7. CONCLUSIONS

Neuro-fuzzy systems not only have powerful approximation abilities for modelling unknown dynamic non-linear systems, but a high level language description of the system can also be obtained. The transparent structure of NF is very useful to study the effect of faults on system characteristics. In this work different approaches for NF based fault diagnosis are studied. An approach is presented which uses TSK and Mamdani NF models to generate residuals. For structure identification GK-Clustering algorithm is used and ten realistic faults are diagnosed in the electro-pneumatic valve actuator model. The main challenges of NF based FDI methods are to minimise false alarms enhance detectability and isolability and minimise detection time by hardware implementation.

## 8. ACKNOWLEDGEMENTS

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