ESANN'2002 proceedings - European Symposium on Artificial Neural Networks
Bruges (Belgium), 24-26 April 2002, d-side publi., ISBN 2-930307-02-1, pp. 501-506

Fault Diagnosis of an Electro-pneumatic Valve Actuator Using Neural Networks With Fuzzy Capabilities

Faisel J Uppal & Ron J Patton

Control & Intelligent Systems Engineering, University of Hull
Hull, HU6 7RX United Kingdom
E-mail: f.j.uppal@eng.hull.ac.uk, r.j.patton@hull.ac.uk

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 an extension to the traditional fault diagnosis methods. This paper discusses the neuro-fuzzy approach to modelling and fault diagnosis, based on the TSK/Mamdani approaches. An application study of an electro-pneumatic valve actuator in a sugar factory is described. The key issues of finding a suitable structure for detecting and isolating ten realistic actuator faults are outlined.

1. Introduction

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 [1]. Neural networks are known to approximate any non-linear function, given suitable weighting factors and architecture. 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 [2]. 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. Neuro-fuzzy (NF) model is a combination of neural network and fuzzy logic to exploit the advantages of both.

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 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 introduces NF

ESANN'2002 proceedings - European Symposium on Artificial Neural Networks
Bruges (Belgium), 24-26 April 2002, d-side publi., ISBN 2-930307-02-1, pp. 501-506

approach, whilst Section 3 describes NF based FDI strategy. Section 4 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 [3, 4]. 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 [5, 6] and Mamdani [7] 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 [8, 9]. 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 data.

3. NF Based Fault Detection and Isolation

Fig. 1 describes a FDI scheme in which several NF models are constructed to identify the faulty & the fault free behaviour of the system.

$$r_i(k) = f\begin{pmatrix} u(k), u(k-1), \ldots u(k-n_u), \\ y(k), y(k-1), \ldots y(k-n_y) \end{pmatrix}; i = 1 \ldots n \qquad (1)$$

Each residual r_i in (1) 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 $fault_r$ is large

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.

ESANN'2002 proceedings - European Symposium on Artificial Neural Networks
Bruges (Belgium), 24-26 April 2002, d-side publi., ISBN 2-930307-02-1, pp. 501-506

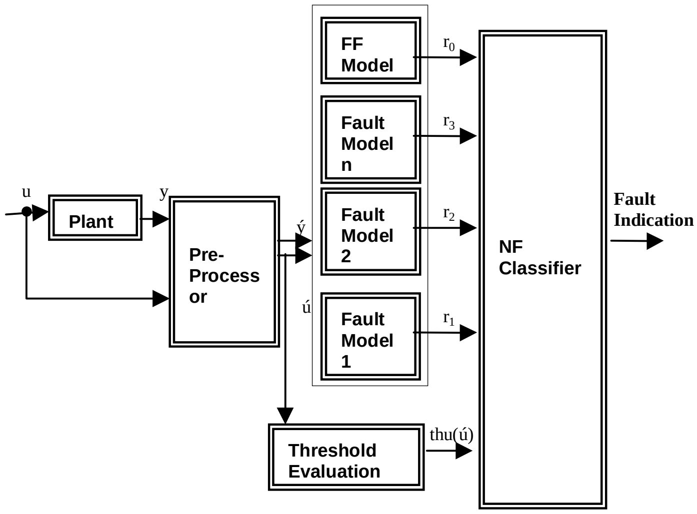

Fig. 1 Neuro-fuzzy based FDI scheme.

Residuals can also be generated by a non-linear dynamic model of the plant that approximates a non-linear dynamic system using local linear models. Such a model can be obtained by *Product space clustering* [10], or tree-like algorithms (LOLIMOT algorithm by Nelles [11]. 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 a model can be described by:

$$y = \frac{\sum_{i=1}^{C} \alpha_i(u_s) \cdot f_i}{\sum_{i=1}^{C} \alpha_i(u_s)} \tag{2}$$

where C is the number of local models and f_i is the i_{th} local linear model given by:

$$\begin{aligned} f_i &= b_{i,1}u(k) + b_{i,2}u(k-1) + \cdots + b_{i,nu}u(k-n_u) + \\ &a_{i,1}y(k) + a_{i,2}y(k-1) + \cdots + a_{i,ny}y(k-n_y) + c_i \end{aligned} \tag{3}$$

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, α_i is the degree to which the i_{th} local model is valid at this operating point. From a_i , b_i and c_i physical parameters like time constants, static gains, offsets etc [8] 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.

ESANN'2002 proceedings - European Symposium on Artificial Neural Networks
Bruges (Belgium), 24-26 April 2002, d-side publi., ISBN 2-930307-02-1, pp. 501-506

4. FDI for an Electro-Pneumatic Valve Actuator

The valve considered for FDI is an electro-pneumatic flow controller in the evaporisation 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. 2):

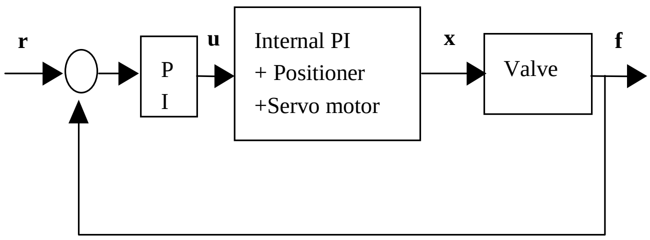

Fig. 2 Main parts of the valve assembly.

<u>The PI controller</u> controls the Positioner & Actuator output to regulate the flow through the valve
<u>Positioner and Actuator</u>: 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.
<u>The Valve</u> is the final element in the assembly that alters the flow according to the stem position.

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

f_1 - External PI proportional gain fault
f_2 - External PI integral gain fault
f_3 - Increased friction of the servomotor
f_4 - Decreased elasticity of 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} - Choked 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. The system's non-linearity is mainly in the dynamics and a transparent TSK model is ideal for this case. The TSK model identified has three locally linear models as consequents. Time constants of these local models are 18, 12 and 8 sec. respectively which show that the system is faster at high values of flow and slower at the low values. From the locally linear models, and the RLSE (*recursive least squares estimator*) 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 that 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

ESANN'2002 proceedings - European Symposium on Artificial Neural Networks
Bruges (Belgium), 24-26 April 2002, d-side publi., ISBN 2-930307-02-1, pp. 501-506

predicted. GK-clustering algorithm [12] is used to partition the input space (Fig. 3), where clusters are projected onto the I/O space to find MF's. Gradient-based optimisation method is used to fine-tune the MFs.

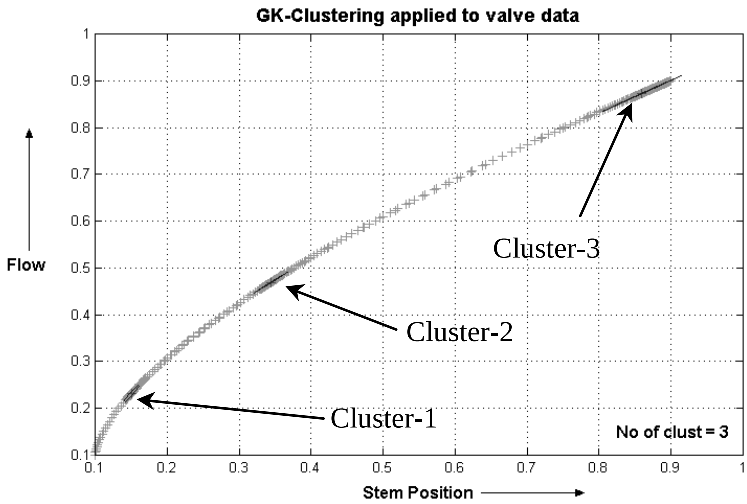

Fig. 3. Valve data clustered in three groups.

<u>Table 1: Fault Isolation</u>

	f_1	f_2	f_3	f_4	F_5	f_6	f_7	f_8	F_9	f_{10}
r_u	Op+ Cl -	Op- Cl+	~	~	~	~	~	~	~	~
r_x	~	~	~	~	~	~	Ch	~	~	~
r_f	~	~	~	~	~	~	~	Op+ Cl -	Op- 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. The 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.

5. 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.

6. Acknowledgements

This work has been conducted through funding from the Framework 5 RTN *DAMADICS* in collaboration with the Lublin sugar factory and Warsaw University of Technology. Faisel Uppal acknowledges funding support through a CVCP ORS (Overseas Research Students) award in the UK, together with a Hull University Open Scholarship.

References

1. R. J. Patton, F. J. Uppal and C. J. Lopez-Toribio (2000). Soft Computing Approaches To Fault Diagnosis For Dynamic Systems: A Survey, *Proc. of 4th IFAC Symposium on Fault Detection Supervision and Safety for Technical Processes, Budapest*, 14-16 June 2000, vol 1, pp. 298-311.
2. R. J. Patton, J. Chen and T. M. Siew (1994). Fault Diagnosis in Non-linear dynamic systems via neural-networks, *Proc. IEE Int. Conference Control '94*, Coventry, UK, 2, 1346-1351.
3. M. Brown and C. J. Harris (1994). *Neuro-fuzzy adaptive Modelling and Control*, Prentice-Hall.
4. Jang J.S. and Sun R. (1995). Neuro-fuzzy modeling and control. *Proc. IEEE.* vol. 83(3), pp 378-405.
5. T. Takagi and M. Sugeno (1985). Fuzzy identification of systems and its applications to modelling and control, *IEEE Trans. Syst., Man, Cybern.*, vol.15.
6. M. Sugeno and G. Kang (1988). Structure identification of fuzzy model, *Fuzzy Sets and Systems*, 26(1), 15-33.
7. E. Mamdani (1976). Advances in the linguistic synthesis of fuzzy controllers, *Int. J. Man-Machine Studies*, vol. 8, pp. 669-678.
8. D. Füssel, P. Ballé, and R. Isermann (1997). Closed loop fault diagnosis based on a non-linear process model and automatic fuzzy rule generation, *Proc. of IFAC symposium on fault detection, supervision and safety for technical process safeprocess'97*, The University of Hull, UK.
9. P. Ballé, O. Nelles and D. Füssel (1997). Fault detection for nonlinear processes based on local linear fuzzy models in parallel and series-parallel model. *Proc. of IFAC symposium on fa ult detection, supervision and safety for technical process safeprocess'97*, The University of Hull, Kingston Upon Hull, UK.
10. R. Babuska (1998). *Fuzzy modelling in control*, Kluwer Academic Publishers.
11. Nelles O. and Isermann R. (1997). Basis function networks for interpolation of local linear models, *IEEE Conference on Decision and Control*, Kobe.
12. D. E. Gustafson and W. C. Kessel (1979). Fuzzy clustering with a fuzzy covariance matrix, in Proc. IEEE Conf. Decision Contr., San Diego, pp761-766.