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A Study on Neuro-Fuzzy Systems for Fault Diagnosis

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Abstract

Fault diagnosis can be facilitated by using either quantitative and qualitative information of the system monitored. This paper presents a novel approach to integrate quantitative and qualitative information in fault-diagnosis, based on the use of neuro-fuzzy systems. In this approach the diagnostic signals - residuals are generated and evaluated via a B-Spline functions network. The configuration adopted allows the designer to both extract and include symbolic knowledge from the trained network to provide reliable diagnostic information. The effectiveness of the proposed diagnosis strategy is illustrated through a simulation study of a non-linear two-tank system.

1. Introduction

Fault Diagnosis has become an issue of primary importance in modern automation. It represents a main pre-requisite for processes to achieve higher reliability, availability, dependability, etc. Traditionally, fault diagnosis depends mainly on the experience of the operator who needs to assimilate a large amount of information from different sources and react rapidly to avoid any hazardous or costly consequences. Over the last two decades, the so-called model-based approach which originated from control theory has been receiving increasing attention both in the research context and in the domain of application studies of real processes (Patton *et al* 1989; Frank, 1990; Patton & Chen, 1994, 1996a, 1997; Gertler, 1993; Patton, Chen & Nielsen, 1995; Isermann, 1997). Requirements for a precise and accurate model imply that any resulting modelling error will affect the fault diagnosis performance (Frank, 1990; Patton & Chen, 1993, 1994, 1997). This is particularly true for highly non-linear systems, which represent the majority of real processes. The

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problem of unmodelled dynamic has, in the past, been addressed by using robust observers. However, the methods presented are usually too complicated or limited to a certain class of nonlinearities (Patton, Chen & Nielsen, 1995; Patton & Chen, 1996a).

Neural-Networks (NNs), on the other hand, can provide an excellent framework for dealing with nonlinear systems (Naidu *et al*. 1990). The main feature of NNs is their ability to model any nonlinear function, given suitable weighting factors and an appropriate architecture. Another property of primary significance to fault diagnosis is the ability of the network to learn from examples, whilst requiring little or no *a priori* knowledge about the structure of the system. However, whilst such a configuration can be extremely well trained on numerical data, heuristic knowledge from experts cannot easily be incorporated. It is also argued that due to their *black box* characteristics, conventional NNs do not give an insight of the behaviour of the system that the user could understand. There have been many researches on the application of NNs to fault diagnosis, e.g. Hoskins & Himmelblau, 1988; Leonard & Kramer (1993), Patton & Chen (1996) and Wang *et al* (1994). Another drawback of substituting the operator's "*intelligence*'' for an *automated* analytical approach, is that the operator's expertise, built up over several years, is simply not used. This is mainly due to the inability of analytical methods to represent symbolic information. A possible solution to this problem is to use qualitative reasoning (Kuipers, 1994). The underlying idea is to build abstract (qualitative) models from a crude description of the system (Shen & Leitch, 1991, 1993). The advantage is that no exact model is required and it can provide an explanation, to the operator, close to the human intuition. The major limitation, however, is that being too general it can produce an amount of results not compatible with the problem being analysed. Moreover, because of their level of abstraction, one would not expect qualitative based approaches to perform as well as quantitative ones in dealing with small incipient faults.

It is the authors' opinion that a robust fault diagnosis system should combine both numerical (quantitative) and symbolic (qualitative) information. In recent years, some researchers have tackled this problem by combining, for instance, parameter estimation or observers with fuzzy logic (Frank and Kuipel, 1993; Isermann & Ulieru, 1993). The main idea has been to generate residuals using either parameter estimation or observers, and allocate the decision making to a fuzzy-logic inference engine. In so doing, it was possible to include symbolic knowledge with the quantitative information and, thereby, minimise the false alarm rate. Indeed, the key benefit of fuzzy-logic is that it lets the operator describe the system behaviour or the fault-symptom relationship with simple if-then rules (Dexter, 1995).

This paper presents a novel approach for fault diagnosis: it combines, in a single framework, both numerical and symbolic knowledge about the process. The method is able to structure a *quantitative model* in a way that qualitative knowledge about the process can be included as well as extracted. The underlying concept is to structure a neural network, which can model highly non-linear systems efficiently, in a fuzzy-logic format. The network can therefore be trained more rapidly, and will also described explicitly the causes of faults. Expert-knowledge can also be included in the same framework. A B-Spline neural-network is used in the unified framework. This network which incorporates both quantitative and qualitative information is used for both residual generation and evaluation in fault diagnosis. In order to illustrate the method developed, the fault diagnosis problem of a laboratory two-tank system is studied in this paper. The paper is organised as follows: In Section 2, the quantitative model-based fault diagnosis and difficulties are discussed. B-Spline neural networks are introduced in Section 3. Section 4 describes residual generation and fault detection using B-Spline neural networks. Fault isolation is discussed in Section 5. Finally, Section 6 describes the application example.

2. Principles and Difficulties of Quantitative Model-based Fault Diagnosis

The aim of a quantitative model-based fault diagnosis system is to generate information about the location and timing of faults in the system monitored, using the measurements available in that system, as well as the *precise* mathematical relationships that relate them. Fig. 1 illustrates the conceptual structure of a model-based fault diagnosis system, which comprises the following main stages (Patton *et al* 1989; Frank, 1990; Patton & Chen, 1994, 1996a, 1997; Gertler, 1993; Patton, Chen & Nielsen, 1995; Isermann, 1997).

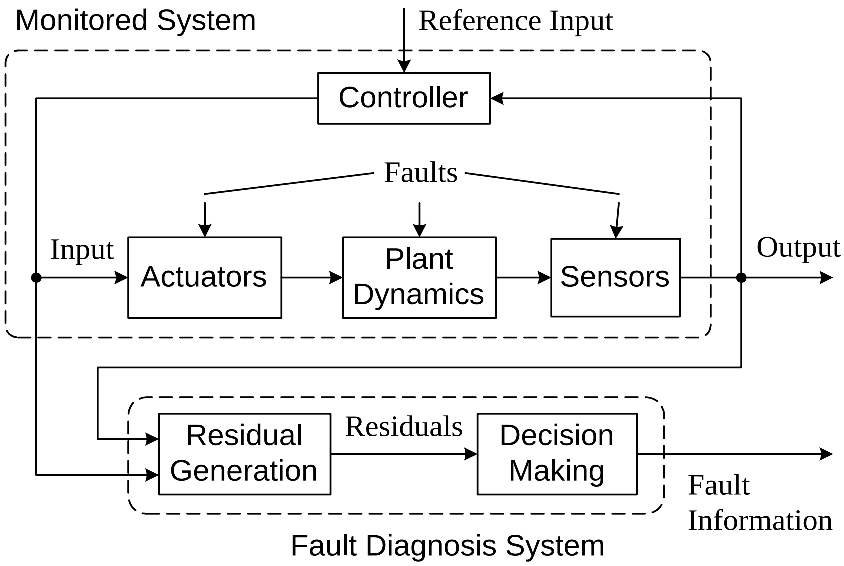

Figure 1: A model-based Fault Diagnosis Structure

Residual Generation: In this stage, a numerical algorithm is used to process the measurable inputs and outputs of the system to generate a diagnostic signal called *residua*l. For that, it uses the model, describing the relationship between those variables in exact mathematical terms, and any inconsistency in this relationship will indicate a fault in the system. The residual must, therefore, be different from zero when a fault occurs and zero otherwise. The system to generate the residual is called *residual generator*.

Decision making: In the second stage, the residuals are examined for the likelihood of faults, and a decision rule is then applied to determine if any fault has occurred. A decision process may be based on a simple threshold test, on the instantaneous values or moving averages of the residuals, or it may consist of methods of statistical decision theory, e.g. likelihood ratio testing or sequential probability testing. The successful detection of a fault is followed by the fault isolation procedure whose aim is to locate the fault. Whilst a single residual signal is sufficient to detect the occurrence of a fault, a set of residuals is required for fault isolation (Patton & Chen, 1996a).

There are three main separate classes of approaches can be used for the design of model-based residual generators (Patton *et al* 1989; Frank, 1990; Patton & Chen, 1994, 1996a, 1997; Gertler, 1993; Patton, Chen & Nielsen, 1995; Isermann, 1997). *(1) Observer-based approaches*: The underlying idea is to estimate the system outputs from the available inputs and outputs of that system. The residual is a weighted difference between the estimated and the actual outputs. The flexibility in selecting the observer gain has been fully exploited in the observer, yielding a rich variety of fault detection schemes. *(2) Parity Relations*: They are based either on a technique of direct redundancy, making use of static algebraic relations between sensor and actuator signals, or, alternatively, upon temporal redundancy, when dynamic relations between inputs and outputs are used. *(3) Parameter estimation:* This approach makes use of the fact that component faults of a dynamic system can be thought of as reflected in the physical parameters as for example friction, mass velocity resistance. It detects faults through the estimation or identification of model parameters, using non-parametric models.

The main assumption when using the above approaches is that an accurate mathematical model of the plant is required. There will be some difficulties to apply quantitative model-based approaches to complex and uncertain systems, since model-reality mismatch can affect the fault diagnosis performance. A way to overcome this, is to design robust algorithms where the effects of modelling errors, on the residual, are minimised and the sensitivity to faults maximised (Frank, 1990; Patton & Chen, 1993, 1994, 1997).

To isolate faults, the residual signal has to be classified further, to indicate which system component has failed. One commonly accepted approach for fault isolation is to generate a set of structured signals (Gertler, 1993, Patton & Chen, 1994, 1996a). The aim is to have each residual sensitive to certain groups of faults and insensitive to others. The relationship between faults and residuals, however, can be nonlinear such as multiplicative faults, making thereby the fault very difficult to isolate.

To overcome the above problem, and make fault diagnosis algorithms more applicable to real systems, neural networks can be used to residual generation as well as decision-making in fault isolation (Patton & Chen, 1996b). Indeed, one of the main features of NNs is their ability to learn from examples. Hence , NNs can be trained to represent relationship between historical data of the residuals (generated too by an NN) and those identified with some known fault conditions. The configuration used by Patton & Chen (1996b) involved a multi-layer feedforward network configuration. However, whilst such a configuration can be extremely well trained on numerical data once that the output is known, symbolic knowledge from experts cannot easily be incorporated. In this paper, we propose to integrate symbolic and quantitative knowledge through a neuro-fuzzy system. This will then combine the learning ability of NNs and the explicit knowledge representation of fuzzy-logic. The application engineer can therefore extract, from the data, a high level language description of the system. Moreover, any heuristic knowledge about the plant can be included.

3 B-Spline Neural Networks and Fuzzy Logic Interpretation

The B-Spline function network has been used as one of effective neuro-fuzzy methods for system modelling and control (Brown & Harris, 1994; Lane *et al*, 1992). This paper takes advantage of this effective tool to generate and evaluate residuals for the purpose of fault detection and isolation. A B-Spline neural-network illustrated in Fig.2 involves input space, basis functions and weight factors.

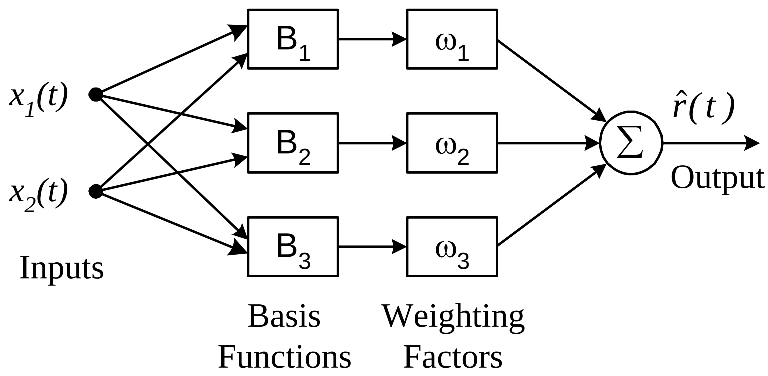

Figure 2: A B-Spine function network with two inputs, 3 basis functions and one output

From Fig,2, it can be seen that all inputs of the network are applied to basis functions which are associative cells defined in the input space, and jointed at breakpoints, referred to as knots. These basis functions perform non-linear transformation of input into a bounded interval [0 1]. Their shape, size and overlap determine the modelling capabilities of the resulting network. The output is a weighted linear combination of basis function outputs. The weighting factors are adjusted by the network training.

Given N partitions of the input within the interval $X = [x_{min}, x_{max}]$, the output of the one dimensional B-Spline network of the form

$$\hat{r} = \sum_{i=1}^{p} B_{n,j}\omega_i \tag{1}$$

can be constructed to approximate the *target signal* $r = F(\boldsymbol{x})$ using a linear combination of the B-Splines, $B_{n,j}(x)$, weighted by coefficients ω_i. The sequence of normalised B-Splines $B_{n,1}(x)$, $B_{n,2}(x)$, ... , $B_{n,p}(x)$ constructed on the knots $\lambda_0, \lambda_1, \ldots, \lambda_N$ can be evaluated from the following recurrent relationship

$$B_{n,j}(x) = \left(\frac{x - \lambda_{j-n}}{\lambda_{j-1} - \lambda_{j-n}} \right) B_{n-1,j-1}(x) + \left(\frac{\lambda_j - x}{\lambda_j - \lambda_{j-n+1}} \right) B_{n-1,j}(x) \tag{2}$$

where $$B_{1,j}(x) = \begin{cases} 1 & if \ x \in I_j \\ 0 & otherwise \end{cases} \tag{3}$$

The B-Spline index *j* is associative with the region of local support $\lambda_{(j-n)} \le x \le \lambda_{(j)}$.

The training of the network, then, consists of finding a set of weighting coefficients ω_i that minimises the cost function

$$J = \frac{1}{N} \sum_{i=1}^{N} (\hat{r}(t) - r(t))^2 \tag{4}$$

where N denotes the number of training sets, whereas *r(t)* and $\hat{r}(t)$ denote the target signal and the network's outputs respectively.

Several approaches can be used to train such a network, depending on whether the learning is done on-line or off-line. In the case studied in here, it is assumed that a set of training data is available to the designer. The weighted Moore-Penrose pseudo-inverse is used to find the optimal set of weighting terms because the model is a linear combination of the set of basis functions.

For a multiple-input-multiple-outputs (MIMO) system, multidimensional B-Spline models are used. They are constructed as tensor products of one-dimensional models. Their corresponding basis functions are formed by a direct multiplication of one-dimensional basis functions defined by Eqs. (2) & (3). For example, a *p* dimensional basis function is defined as

$$B(x) = \prod_{i=1}^{p} B_p(x_p) \tag{5}$$

It is interesting to note that the output of the network, as given by Eq. (1), is very similar to that of a fuzzy associative memory network. Indeed, considering a fuzzy rule, R_{ij}, such as

R_{ij}: IF (x is A_i) THEN (r is B_j) (c_{ij}) ($i=1, ..., p; j = 1, ..., q$)

where A_i and B_i denote respectively fuzzy sets in the input and output partition space, q is the input partition space number, p is the output partition space number, and c_{ij} the level of confidence in the rule R_{ij} being true. It can be shown that the output of a continuous fuzzy rule is given by

$$r(x) = \sum_{i=1}^{p} \mu_{A_i}(x) \omega_i \tag{6}$$

$$\omega_i = \sum_{j=1}^{q} c_{ij} y_j^c \tag{7}$$

where y_j^c is an observation of x where the confidence level is c_{ij}. Brown & Harris (1994) showed that, given a set of optimal B-Spline networks weights ω_i, it is possible to find the equivalent fuzzy representation with the coefficients c_{ij} given by the relation:

$$c_{ij} = \mu_{B_j}(\omega_i) \tag{8}$$

This relation, between B-Spline networks and fuzzy logic, is very important. It shows that, not only a B-Spline network can be trained, from numerical data, but symbolic knowledge can be included (or extracted) from it too. This very important feature allows to integrate both numerical and qualitative knowledge within a single framework.

4. Residual Generation and Fault Detection using B-Spline Networks

As discussed in Section 2, the main task of fault diagnosis is to generate diagnostic signals - residuals. There have been several researches on generating residuals for nonlinear dynamic systems via neural networks, for example, Patton & Chen (1996b) proposed a neural network-based residual generation structure based on multi-layer feedforward networks. The underlying concept is to train the network to recognise the occurrence of a fault and to find the optimal function that maps the system inputs-outputs to a residual signal:

$$\mathrm{r}(t) = F(\vec{\mathrm{u}}(t), \vec{\mathrm{y}}(t)) \tag{9}$$

where $\vec{\mathrm{u}}(t) = [\mathrm{u}(t), \mathrm{u}(t-1), \ldots, \mathrm{u}(t-m)]^T$ and $\vec{\mathrm{y}}(t) = [\mathrm{y}(t), \mathrm{y}(t-1), \ldots, \mathrm{y}(t-n)]^T$ are the input and output of the system over a time-window. The input of the network includes past as well as current values of the measurements, to capture temporal information.

In this study, a B-Spline neural-network is used to diagnose faults in the non-linear system and overcome the disadvantage of multi-layer feedforward networks. To be more specific, the measured inputs and outputs of the system are processed through an associative memory network, as opposed to a multi-layer feedforward network of Patton & Chen (1996b). The advantages of associative memory network are computationally efficiency in training and the ability of incorporating heuristic knowledge.

It is important to note that the aim of the fault detection observers (Patton & Chen, 1993, 1996a; Patton, Chen & Nielsen, 1995), or residual generators, is not to estimate the state of the plant but rather to respond promptly to the occurrence of a fault. Hence, the residual generator should produce a value of 1 when a fault develops in the system, and 0 otherwise. In such an approach, it may be said that the network used is an alternative to the traditional fault detection observers.

An important feature of a neural-network is that it will learn during a training session made over several training cycles, with training data coming from different operating points. However before the training is started, the order of the B-Spline network needs to be chosen. In this paper, a network with a second order basis function, and 2 linear knots, was chosen. As it can be seen from Fig. 3, such a configuration permits to divide the normalised input space into 3 linguistic variables *Small*, *Medium* and *Large.*

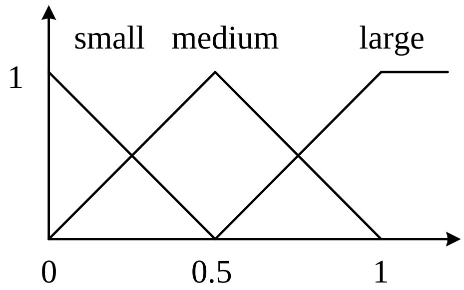

Figure 3: B-Spline functions defined over the normalised Input Space

Once the training is performed, a set of optimal weights ω_i *(i=1, .., p)* are used to derive the corresponding fuzzy description of the residual generator. Moreover, since the basis functions can be interpreted linguistically, a qualitative model of the residual generator can be derived. This provides the operator with an explanation about the cause of the fault which is more understandable to him/her than using crisp neural-networks.

5. Fault Isolation via B-Spline Function Networks

In this section, the B-Spline neural-network is used to locate faults in the process (fault isolation). The locations of faults to be diagnosed are assumed to be known to the designer. Therefore, the designer can simulate the system with all possible faults to generate corresponding training data. The isolation network has as many outputs the number of different system behaviours. Hence, for a system with 2 classes of faults, the output of the network will be a vector of dimension 3; this includes the models associated with the two faulty situations as well as the *healthy* situation.

To train the network, we need to decompose it into a set of *(M+1)* multi-inputs-single-output (MIMO) sub-models, where *M* is the number of faulty classes, and find the set of optimal weighting factors with each sub-model. When the network is applied to a test point, $(\vec{u}(t),\vec{y}(t))$ the network's output, *Flag*, is a real vector of dimension *(M+1)*. It can be seen from Fig. 4 that each component of that vector, $Flag_i$ (i=1,2,..., M) is identified with a class of behaviour, which can be either a *Fault i,* or the nominal model. When the system is operating in its nominal condition, all the network outputs are zero except the last one. However, when a specific fault develops in the system the corresponding output will deviate from zero, whereas the output flags become zero, confirming that the system is no longer healthy. The training data can be obtained from a numerical simulation where a number of different faulty scenarios are simulated. As for network training, there are B-Spline training routines readily available in the Neural Networks Toolbox for Matlab.

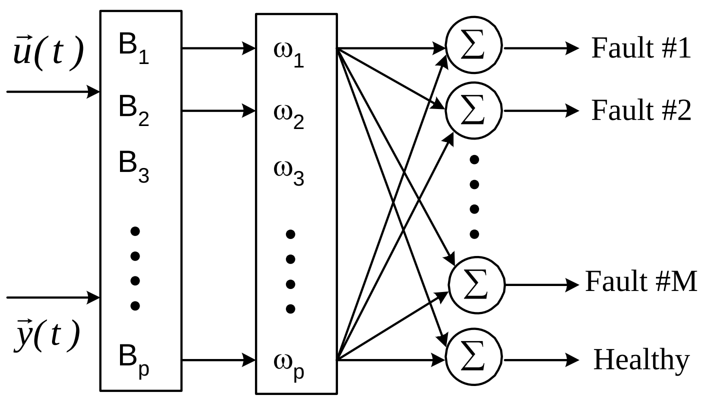

Fig. 4: Network-Architecture used for fault-isolation

6. Fault Diagnosis of a Two-tank System

To evaluate the performance of the fault detection and isolation scheme proposed, a laboratory two-tank system (see Fig.5) is chosen. The system is widely accepted as a laboratory demonstrator and has the industrial parallels including the cooling water circuits of chemical distillation columns and chemical reactors in general, and feed water systems in power stations. The 2-tank system, although simple in operation, enables generic concepts to be developed and, very importantly, to be physically tested. The simplicity of the system does not obscure the fundamentals and basic ideas which are being studied. The system presents realistic challenges such as non-linearity and modelling uncertainty.

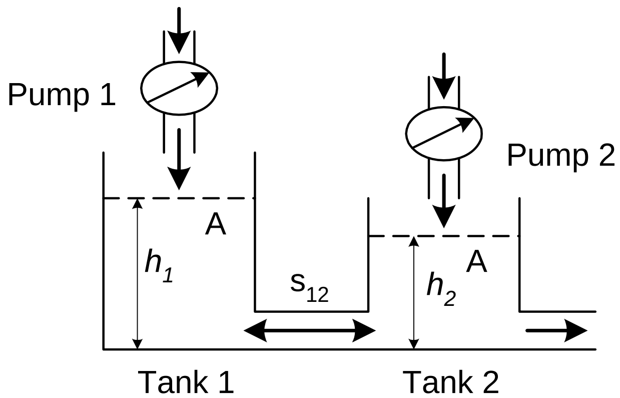

Fig. 5: Two tank system

The two-tanks-system consists of two interconnected tanks, connected to each other through connecting pipes of circular cross-section. Two pumps P_1 and P_2 control the incoming mass-flows Q_1(t) and Q_2(t). The two tanks are equipped with piezo-resistive pressure transducers for measuring the level of liquid, h_1(t) and h_2(t). For the dynamic model, the incoming mass flows Q_1(t) and Q_2(t) are defined as inputs, while the two measurements h_1(t) and h_2(t) are considered as outputs. The dynamic model is then derived using the incoming and outgoing mass flows and is described by the following differential equations:

$$A\frac{dh_1(t)}{dt} = Q_1(t) - a_1 s_{12}(h_1(t) - h_2(t))\sqrt{2g\left|h_1(t) - h_2(t)\right|} + Q_{f1}(t)$$
$$A\frac{dh_2(t)}{dt} = Q_2(t) + a_1 s_{12}\, sgn(h_1(t) - h_2(t))\sqrt{2g\left|h_1(t) - h_2(t)\right|} + Q_{f2}(t)$$

The Q_{fi}(t) (i=1,2) denote the additional mass flows caused by leaks .

The fault diagnosis B-Spline neural-network is trained *off-line*, using a set of data from the simulation. After a set of optimal weighting terms ω_i is found, the network is simulated, *on-line* to monitor the system. Faults are then introduced, and the performance of the fault diagnosis algorithm is assessed.

Fig. 6 shows the residual response to an impulse input of 25 seconds. A leak has also been included at time intervals indicated. It is interesting to note that, the fault signature is very clear in the residual response, *r(t)*, generated by the B-Spline network, as it shows a significant response each time a fault occurs.

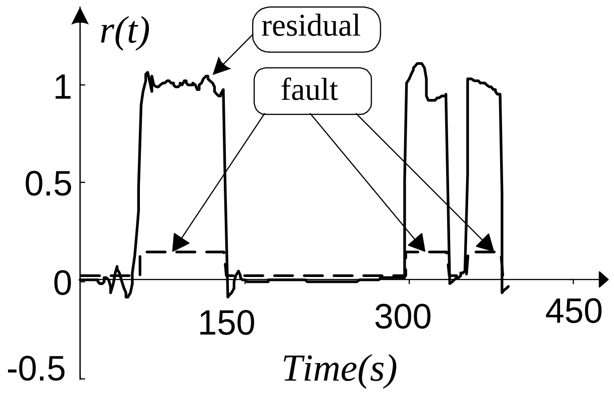

Figure 6: Residual response

As mentioned earlier, it is possible to extract symbolic knowledge from the residual generator. This is illustrated in following table where 2 rules are extracted from the B-Spline neural-network based residual generator. The universe of discourse of the residual generator output is divided into two overlapping intervals delimiting the linguistic variables *Healthy* and *Faulty*.

Table: Qualitative Model of the Residual Generator

IF h_1 Small & h_1(t-1) Small & h_2(t) Small & u(t) Large Then Plant is Faulty	(1.00)
IF h_1 Small & h_1(t-1) Small & h_2(t) Small & u(t) Small Then Plant is Healthy	(0.998)

Once the residual generator has been trained, it is also possible to include some qualitative knowledge about the plant. Such knowledge can either be obtained from the human expert, or generated from a qualitative model of the plant using qualitative reasoning physics. To illustrate this idea, let us consider the case where the cross pipe is jammed and the operator does not have any data associated with that behaviour, except some heuristic rules gained through experience. These rules can be expressed as follows:

If $Q_1(t)$ *High* and $h_1(t)$ *High* and $h_1(t-1)$ *High* and $h_2(t)$ *Small* the System *Faulty* ($c=0.9$)

The aim is then to find the optimal weighting term *w* associated with the above fuzzy relation. For that purpose, fuzzy output membership functions are defined in the output universe of discourse. In this application it is assumed that the system falls in either a *Faulty* or a *Normal* behaviour (although more behaviours could also be considered) and therefore only two functions are chosen. The weighting term, *w*, is then taken to be as the projection of the *rule confidence index, c,* (equal to *0.9* for this example) on the universe of discourse. For the particular example considered above, the corresponding weighting term was found to be $w=0.9$.

Fault Isolation is usually performed via a two stage mapping-process of the measured variables: the first one for generating residuals, using either observers, parameter estimation or parity space (Patton, Chen & Nielsen, 1995), the second for detecting and/or isolating the fault. In this paper, a single mapping was performed via the use of a B-Spline neural-network. The underlying concept is to train the network to classify faults directly from the measured inputs and outputs of the system. For that, a set of training data associated with different classes of faults needed to be generated. The network's output is, then, a vector, whose elements indicate the truth in a certain model being true. The following classes of behaviour were identified in our application.

Fault 1: This fault is defined as being a leak in tank 1. A value of 1 in the signal, *Flag 1*, indicates that a leak in tank 1 has occurred.

Fault 2: Similarly to Fault 1, this class is associated with a leak in tank 2. A value of one in the signal Flag2 indicates that the tank 2 is leaking.

Fault 3: The third fault considered in this work is where the pipe connecting the two tanks is jammed. The signal associated with that class of fault is *Flag3*.

Healthy: The redundant signal, *Flag 4,* associated with the Healthy operating condition, indicates if a fault (any fault) has occurred in the system.

The network was trained to identify the above faults, and then tested, on-line, to detect and isolate faults. Figs. 7-9 show the responses of the different outputs to the three faults. It can be seen that, at each time, only the signal associated with the fault's class deviates from the zero value.

After the training of the network has been completed, it is possible to find the causes of each fault. This is obtained by finding the equivalent fuzzy representation of the B-Spline network. The human operator can then modify such a knowledge, or even add any new information that has been missed during the training, a new fault for example.

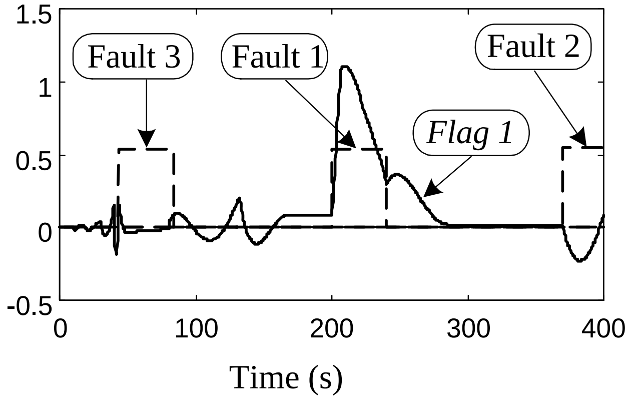

Figure 7: Flag 1 response to faults

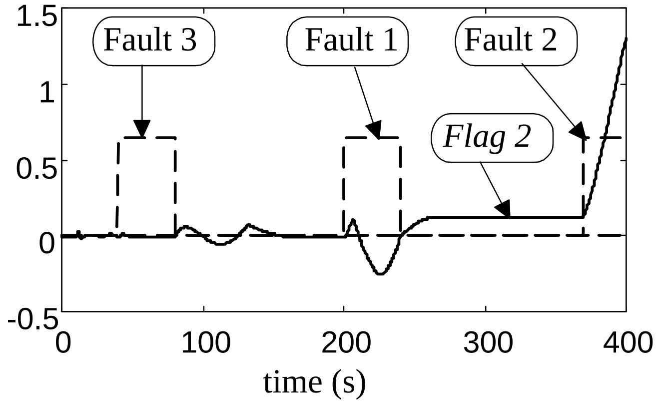

Figure 8: Flag2 response to faults

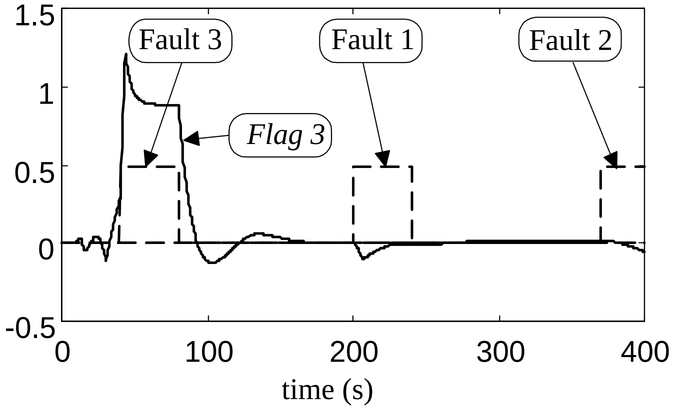

Figure 9: Flag 3 response to faults

7 Concluding Discussions

This paper presented a novel approach for automatic diagnosing faults. The approach, based on neuro-fuzzy systems, has the advantage of a neural network but provides, also, information close to human common sense. This, indeed, allows the designer to find what the network has learnt, and check if the explanation provided by the network has a physical explanation; rules, and therefore weighting coefficients, can be altered if necessary. Moreover, because of the analogy between fuzzy-logic systems and B-Spline neural-networks, the designer can also include some heuristic (qualitative) knowledge about the either the plant or the fault. The combination of qualitative and quantitative information through the integrated framework proposed provides a powerful tool for reliable fault diagnosis. The effectiveness of the scheme has been illustrated by a laboratory two-tank system with nonlinear modelling complexity. The scheme can be applied to a wide range of complex nonlinear dynamic systems with uncertain factor. The main advantage of the scheme over quantitative approaches such as the NN-based approach using by Patton and Chen (1996b) is robustness due to the introduction of heuristic information. Comparing with the study of Patton and Chen (1996b), where a NN-based approach is applied to a three tank system, the scheme presented in here has greater robustness against uncertainty such as measurement noise. Moreover, the approach used in this study is computationally efficient over the multi-layer feedforward neural networks used by Patton & Chen (1996b). The main disadvantage of qualitative approach is ambiguity where dealing with small incipient faults. As the scheme used in this study is mainly based on a quantitative model with some assistance of heuristic information, the shortcoming of qualitative approaches is eliminated. Although further objective comparative studies of this scheme and other qualitative approaches are needed, it is the authors' belief that best diagnostic performance can be achieved by combining qualitative and quantitative approaches.

8. Acknowledgements

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