SOFT COMPUTING APPROACHES TO FAULT DIAGNOSIS FOR DYNAMIC SYSTEMS: A SURVEY

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Abstract: Recent approaches to fault detection and isolation for dynamic systems using methods of integrating quantitative and qualitative model information, based upon soft computing (SC) methods are surveyed. In this study, the use of SC methods is considered an important extension to the quantitative model-based approach for residual generation in FDI. When quantitative models are not readily available, a correctly trained neural network (NN) can be used as a non-linear dynamic model of the system. However, the neural network does not easily provide insight into model behaviour; the model is explicit rather than implicit in form. This main difficulty can be overcome using qualitative modelling or rule-based inference methods. For example, fuzzy logic can be used together with state space models or neural networks to enhance FDI diagnostic reasoning capabilities. The paper discusses the properties of several methods of combining quantitative and qualitative system information and their practical value for fault diagnosis of real process systems. *Copyright © 2000 IFAC*

Keywords: Soft computing methods, fault-diagnosis, FDI, computational intelligence, AI methods

1. INTRODUCTION

There is an increasing demand for man-made dynamical systems to become safer and more reliable. These requirements extend beyond normally accepted safety-critical systems of nuclear reactors, chemical plants or aircraft, to new systems such as autonomous vehicles or fast rail systems. The early detection of faults can help avoid system shut-down, breakdown and even catastrophes involving human fatalities and material damage. A system which includes the capacity of detecting, isolating, identifying or classifying faults is called a *fault diagnosis* system. During the last two decades many investigations have been made using analytical approaches, based on quantitative models. The idea is to generate signals that reflect inconsistencies between nominal and faulty system operation. Such signals, termed *residuals*, are usually generated using analytical approaches, such as observers (Patton *et al* 2000, Chen & Patton, 1999), parameter estimation (Isermann, 1994) or parity equations (Gertler, 1998) based on analytical (or functional) redundancy. Considerable attention has been given to both research and application studies of real processes, using analytical redundancy as this is a powerful alternative to the use of repeated hardware (hardware or software redundancy).

The monitoring of faults in feedback control system components has come to be known as *fault detection and isolation* (FDI). The procedure of generating control action which has a low dependency on the presence of certain faults is known as *fault-tolerant control.* The FDI unit provides the supervision system with information about the onset, location and severity of any faults. Based on system inputs and outputs together with fault decision information from the FDI unit, the supervision system will reconfigure the sensor set and/or actuators to isolate the faults, and tune or adapt the controller to accommodate the fault effects.

Early detection and isolation of small, incipient (rather difficult to detect) faults can be achieved with model-based processing of all measured variables, using either qualitative or quantitative modelling. Neural networks and fuzzy logic techniques are now being investigated as powerful modelling and decision making tools, along with the more traditional use of non-linear and robust observers, parity space methods and hypothesis-testing theory.

Requirements for precise and accurate analytical model imply that any resulting modelling error will affect the performance of the resulting *fault detection and isolation* (FDI) scheme. This is particularly true for non-linear systems, which represent the majority of real processes.

To circumvent this precision problem (at least in part) more abstract models, based on qualitative physics (de Kleer & Williams, 1987; Shen & Leitch, 1993, Kuipers, 1994, Lunze *et al.*, 1999) may be used. Alternatively fuzzy-logic rules may be developed to either assist or replace the use of a model for diagnosis (Dexter, 1995). The key advantage of fuzzy logic is that it enables the system behaviour to be described by "*if-then*" relations.

Some research has been based upon neural networks which can be trained to reproduce a specified system behaviour from the data sets alone. Neural networks can, indeed, provide an excellent framework for dealing with non-linear systems (Naidu, Zafirou & McAvoy, 1990). The main feature of neural networks are their ability to model any non-linear function, given suitable weighting factors and an appropriate architecture.

However, whilst such a configuration can be 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 neural networks do not give an insight into the behaviour of the system which is sufficiently comprehensible by the operator. Another drawback of substitution the operator's "intelligence" by 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.

In the authors' opinion a robust FDI system should combine both numerical (quantitative) and symbolic (qualitative) information. Some investigators tackled this problem by combining parameter estimation or observers with fuzzy logic (Frank & Kuipel, 1993; Isermann, 1994). 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 has been 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. Here we use the term "soft computing" (SC) for all methods employing computational intelligence algorithms, e.g. fuzzy logic, neural networks, neuro-fuzzy schemes, evolutionary programming, etc.

This paper gives an outline of SC methods which are considered a powerful extension to quantitative/analytical approaches to fault detection and isolation (FDI) for dynamic systems.

One approach is to use a fuzzy rule-base to select the dynamic model which is most appropriate for a particular operating point (Wang *et al.*, 1995; Tanaka *et al.*, 1996). This is the so-called *fuzzy inference multiple-model* approach. The idea has recently been applied to FDI problems by Lopez-Toribio *et al.* (1998).

It is important to structure a *quantitative model* in a way that qualitative knowledge about the process could be included as well as extracted. These can be achieved using a neuro-fuzzy approach. The underlying concept is to structure a neural network, which can model highly non-linear systems efficiently, in a fuzzy-logic format; the network could therefore be trained more rapidly and will also provide a linguistic description about the causes of faults. The B-spline network can be a suitable network architecture for this problem due to an interesting equivalence relation with the function of fuzzy rule sets (Brown & Harris, 1994a). The difficulty with this approach is the rapidly increasing complexity of the rule base with system order and complexity.

2. MODEL-BASED FDI PRINCIPLES

The aim of a quantitative model-based fault diagnosis is to generate information about the location and timing of a fault, 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.

Residual Signal:

$$r(s) = H_u u(s) + H_y y(s) \qquad (1)$$

Objectives:

choose H_u & H_y so that

$r(s) = 0$ when no fault occurs

$r(s) \neq 0$ when a fault occurs

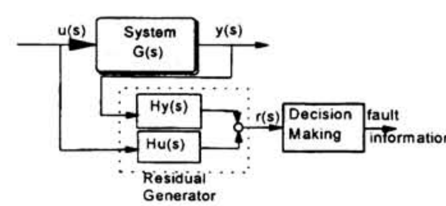

Fig. 1 Model-based Fault Diagnosis

1. **Residual Generation**: This is an algorithm which processes the measurable inputs and outputs of the system to generate the residual signal.
2. **Decision making**: The residuals are, then, 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.

- **Observers**: The underlying idea is to estimate the system outputs from the available inputs and outputs (Patton, 1997). The residual will then be 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.

- **<u>Parity Relations</u>**: 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.

- **<u>Parameter Estimation</u>**: 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. Faults are detected by estimating parameters of non-parametric models.

The main assumption made when using the above methods is that a precise mathematical model of the plant is required. This makes quantitative model-based approaches very difficult to use in real systems, since any un-modelled dynamics can affect the performance of the FDI scheme. A way to overcome this, is to design robust algorithms where the effects of disturbances, on the residual, are minimised and the sensitivity to faults maximised. A lot of approaches had been developed including *unknown input observers* and *eigenstructure assignment observers* (Patton *et al* 2000; Chen & Patton, 1999), frequency domain techniques for robust FDI filters such as H_∞ (Edelmeyer *et al.*, 1997) and the minimisation of multi-objective functions (Chen, Patton & Liu, 1997).

3. FDI VIA NEURAL NETWORKS

To overcome some of the difficulties of using mathematical models, and make FDI algorithms more applicable to real systems, the neural network can be used to both generate residuals and isolate faults (Chen & Patton, 1999). A neural network is a processing system that consists of a number of highly interconnected units called neurons. The neurons are interconnected by a large number of 'weighted links'. Each neuron can be considered as a mathematical function that maps the input and output space with several inputs. The inputs are connected to either the inputs of the system or the outputs of the other neurons in the system. The output of one neuron effects the outputs of other neurons and all neurons connected together can perform complex processes.

Indeed, one of the main features of neural networks is their ability to learn from examples. Hence, they can be trained to represent relationships between past values of residual data (generated by another neural network) and those identified with some known fault conditions. The configuration used by Chen & Patton (1999) involved a multi-layer feed-forward network configuration (Fig. 2).

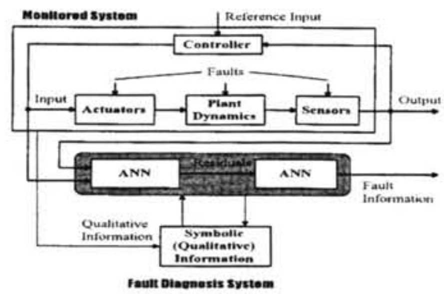

Fig. 2 Neural networks scheme for FDI

Whilst this configuration can be well trained on numerical data once that the output is known, symbolic knowledge from experts cannot easily be incorporated.

The mathematical model used in traditional FDI methods can be very sensitive to modelling errors, parameter variation, noise and disturbance. However, no mathematical model of the system is needed to implement a neural network. Online training makes it possible to change the FDI system easily when changes are made in the physical process, control system or parameters. A suitably trained neural network can *generalise* when presented with inputs not appearing in the training data. Neural networks have the ability to make intelligent decisions in cases of noisy or corrupted data. They also have a highly parallel structure, which is expected to achieve a higher degree of fault-tolerance then conventional schemes (Hunt *et al.*, 1992). Neural networks can operate simultaneously on qualitative and quantitative data and they are readily applicable to multivariable systems. Neural networks can also be applied for process condition monitoring, where the focus is on small irreversible changes in the process which develop into bigger faults. Yin (1993) demonstrated the application of MLP and Kohonen self-organising feature map (KFM) to predictive maintenance or condition-based maintenance of electrical drives, particularly induction motors. The first method utilises supervised learning and in the second the learning is unsupervised.

3.1 Application Studies

Neural networks have been successfully applied to many **applications** including fault diagnosis of non-linear dynamic systems (Wang, Brown & Harris, 1994; Dong & McAvoy, 1996). Multi-layer perceptron (MLP) networks are applied to detect leakages in electro-hydraulic cylinder drive in a ***fluid power system*** (Watton & Pham, 1997). They showed that maintenance information can be obtained from the monitored data using the neural network instead of a human operator. Crowther *et al.* (1998), showed in an application of a neural network to fault diagnosis of **hydraulic actuators,** that experimental faults can be diagnosed using neural networks trained only on simulation data. Neural networks are applied to detect the internal leakage in the **control valves** and **motor faults** in process plants (Sharif & Grosvenor, 1998).

Kuhlmann *et al* (1999) presented the principle of the Device-Specific ANN (DS-ANN) approach to fault diagnosis. The basic principle of the DS-ANN approach is that neural networks are trained for dealing with certain basic groups or electrical devices (e.g. lines, transformers, busbars etc). Weerasinghe *et al* (1998) investigated the application of a single neural-network for the diagnosis of non-catastrophic faults in an industrial nuclear processing plant operating at different points. Data-conditioning methods are investigated to facilitate fault classification, and to reduce network complexity. Maki & Loparo (1997) presented detection and diagnosis of faults in industrial processes that require observing multiple data simultaneously. The main feature of this approach is that the fault detection occurs during transient periods of process operation. Vemuri & Polycarpou (1997) investigated the problem of fault diagnosis in rigid-link robotic manipulators with modelling uncertainties. A learning architecture with sigmoidal neural networks was used to monitor the robotic system for any off-nominal behaviour due to faults. Butler *et al* (1997) discussed the use of a new neural network *supervised clustering method* to perform fault diagnosis for power distribution networks. The neural network proposed performs fault type classification, faulted feeder and faulted phase identification, and fault impedance estimation for grounded and ungrounded distribution networks.

Neural networks have also been applied to the problem of joint faults in robots, using pattern recognition. The joint-backlash of robots is diagnosed by monitoring its vibration response during normal operation (Pan *et al.* 1998). James and Yu (1995) used a neural network for the condition monitoring and fault diagnosis of a high-pressure air compressor valve. The neural network-based FDI scheme can also show when further increases in fault levels might be likely, thus giving the operator time to take necessary action (Boucherma, 1995).

Dynamical neural networks (Korbicz *et al* 1998) are applied to on-line fault detection of power systems, aircraft systems, chemical plants and nuclear reactors which are highly non-linear complex.

3.2 Strategies for Fault Diagnosis

It is clear that neural networks can be applied to fault diagnosis using different approaches. *Pattern recognition* approach and *residual generation-decision making* are the most common ones. The second approach is generally more suitable for dynamic systems and comprises *residual generation* and *decision making* stages in just the manner outlined in section 2 of this paper. In the first stage the residual vector **r** is determined in order to characterise each fault. Ideally, the neural network models identify all classes of system behaviour. The second stage, *decision making* or *classification* processes the residual vector **r** to determine the location and occurrence time of the faults. Chen and Patton (1999) also showed that a single neural network can be used for both stages simultaneously, with increased training time and complexity. Fault isolation requires that the training data are available for all expected faults in terms of residual values or system measurements.

The neural network can be used for classification in conjunction with other residual generating methods e.g. non-linear observers. Neural networks have been successfully applied in state and parameter based FDI schemes (Han & Frank , 1997; Ficola *et al* 1997). Han and Frank (1997) proposed a *parameter estimation based FDI using neural networks* in which physical parameters are estimated by applying the neural network universal approximation property applied to the measured I/O data. The deviations from normal values are then used for fault diagnosis. It is assumed that the faults in the monitored process can be described as changes in the parameter vector and the nominal parameter values are known in advance or can be estimated online (*e.g.* via recursive least-squares method). A linear model of the system can be described as:

$$\begin{aligned} \dot{X}(t) &= A(\theta(t))X(t) + B(\theta(t))U(t) + \xi(t) \\ Y(t) &= C(\theta(t))X(t) + D(\theta(t))U(t) + \eta(t) \end{aligned} \tag{2}$$

or

$$Y(t) = H\begin{pmatrix} \frac{d^{(n)}Y}{dt^n}, \frac{d^{(n-1)}Y}{dt^{n-1}}, \dots, \frac{dY}{dt}, \\ \frac{d^{(m)}Y}{dt^m}, \frac{d^{(m-1)}Y}{dt^{m-1}}, \dots, U \end{pmatrix}\theta(t) + \varepsilon(t) \tag{3}$$

where $X \in R^n$, $Y \in R^m$, $\theta \in R^p$ are the state, output, model parameter vectors and $\xi \in R^n$ and $\eta \in Rm$ are the process and measurement noise signals. $A(\theta)$, $B(\theta)$, $C(\theta)$, $D(\theta)$ and H( ) are known function matrices. (1) is suitable for FDI with state estimation whilst (2) is suitable for parameter estimation based FDI. Faults in the process can be described as the change in the parameter vector $\Delta\theta = \hat{\theta} - \theta_o$, where $\hat{\theta}$ and θ_o are the estimated and nominal parameter vectors.

Neural networks have been successfully applied to the on-line FDI of industrial processes. Fuente & Vega (1999) used a neural network for FDI of a biotechnological process. Real data from experiments on the plant were used together with on-line estimation. The back-propagation algorithm was used to analyse the frequency content of some fault-indicating signals derived from the identification step. This gave rise to correct detection and isolation of each fault. Gomm (1998) described an adaptive neural network that continually monitors and improves its performance on-line as new fault information becomes available. New nodes are automatically added to the network to accommodate novel process faults after detection, and on-line adaptation is achieved using recursive linear algorithms to train selected network parameters.

3.3 Taxonomy of Neural Networks

There is a large number of neural network architectures in use. Feed-forward, recurrent, Radial Basis Function (RBF), fuzzy, B-spline, dynamic, competitive and probabilistic neural networks are among the most frequently used structures for fault diagnosis. Li *et al* (1999) described a method to diagnose the most frequent faults of a screw compressor and assess magnitude of these faults by tracking changes in the compressor dynamics. Yu *et al* (1999) investigated semi-independent neural model, based on an RBF network, to generate enhanced residuals for diagnosing sensor faults in a reactor. Narendra *et al* (1998) also used the RBF network architecture for fault diagnosis in a HVDC system. A new pre-classifier was proposed which consists of an adaptive filter (to track the proportional values of the fundamental and average components of the sensed system variables), and a signal conditioner which uses an expert Knowledge Base (KB) to aid the pre-classification of the signal.

Other networks used in recent applications include Dynamic Back-propagation networks (Narendra, 1996) and Cerebellar Model Articulation Controller (CMAC) Network (Leonhardt *et al.*, 1995; Brown & Harris, 1994b). Each of these architectures offers different characteristics to suit distinct applications. Recent research focuses on networks that can optimise their structure during training. Ren and Chen (1999) proposed a new type of neural network in which the dynamical error feedback is used to modify the inputs of the network.

3.4 Design issues of applying neural networks for fault diagnosis

As discussed earlier, neural networks provide essentially a "black box" signal processing structure, which do not show rules governing their operation and there is no visibility as to their real behaviour (from an input-output point of view). This does not enable the user to understand the system and predict its behaviour in uncertain situations. On the other hand, B-spline networks can be used to extract and include some heuristic knowledge about the system.

The training time required for a specific application and the complexity of the training algorithm present further limitations. The earlier back-propagation algorithm used to train MLPs; requires an excessive training time and is generally an off-line method for training. RBF networks are capable of on-line adaptive training if required (Wilson, 1998) but use large numbers of neurons if the I/O space is large. To accelerate convergence, state variables with additional terms can be used in training (Watton & Pham, 1997).

Neural networks which use neurons as membership functions, e.g. RBF and B-spline networks, do not generalise well when presented with data outside the training I/O space. MLP and Fuzzy Logic based systems on the other hand tend to generalise in a better way. On-line training should be used to update such networks (Wilson, 1998).

If some unknown fault conditions appear, the neural classifier is no longer valid because it is not trained to classify this type of fault. Adaptive training algorithms should be used with systems requiring on-line training.

It is not usually possible to acquire all the faulty data for neural network training. Thus unsupervised training, which uses a Kohonen network and the Counter-propagation (CPN) network (Dalmi *et al.*, 1999), is necessary in order to classify the faults not known *a priori*. A combined artificial neural network and expert system tool (ANNEPS) is developed (Wang, 1998) for transformer fault diagnosis using dissolved gas-in-oil analysis (DGA). ANNEPS takes advantage of the inherent positive features of each method and offers a further refinement of present techniques.

3.5 Hybrid neural networks

Neural network-based FDI methods usually require pre-processing or signal conditioning algorithms to reduce the effect of noise and disturbance and to enhance the fault features. Many other techniques have been combined with neural networks, including fuzzy logic, genetic algorithms and adaptive modelling etc. Aminian *et al* (2000) developed an analog-circuit fault diagnostic system based on back-propagation neural networks using wavelet decomposition, principal component analysis, and data normalisation as pre-processors. The proposed system has the capability to detect and identify faulty components in an analog electronic circuit by analysing its impulse response. Pantelelis *et al* (2000) developed simple finite element (FE) models of a turbocharger (rotor, foundation and hydrodynamic bearings) combined with neural networks and identification methods and vibration data obtained from real machines towards the automatic fault diagnosis. Liu(1999) used an extended Kalman filter (EKF) and neural network classifier for FDI. Network inputs are the process I/O data, such as pressure and temperature, parameters estimated by EKF, and state values calculated by dynamic equations, whilst network outputs are process fault scenarios. Zhao *et al* (1998) presented a multidimensional wavelet (MW) with its rigorously proven approximation theorems. Taking the new wavelet function as the activation function in its hidden units, a new type of wavenet called multidimensional non-orthogonal non-product wavelet-sigmoid basis function neural network (WSBFN) model is proposed for dynamic fault diagnosis. Based on the heuristic learning rules presented by Zhao *et al* (1998), a new set of heuristic learning rules is presented for determining the topology of WSBFNs. Izhao *et al* (1997) proposed the wavelet-sigmoid basis neural network (WSBN) with expert system (ES) for dynamic fault diagnosis (DFD). Ye & Zhao (1996) proposed. A hybrid intelligent system which integrates neural networks with a procedural decision-making algorithm to implement hypothesis-test cycles of system fault diagnosis.

3.6 Multiple fault detection

Neural networks have been found to give more information with regard to multiple-fault conditions than some other methods (steady-state position error, time series analysis). Some neural networks are applied to diagnose multiple faults in the processes but generally it is much more difficult to diagnose such faults in a process because the training data needed becomes very large. Maidon *et al* (1999) developed a technique for diagnosing multiple faults in analog circuits from their impulse response function using a fault dictionary. A technique is described (Ogg *et al* 1998) for diagnosing multiple faults in analogue circuits from their impulse response function using multi-layer perceptrons, in terms of a specific example. A Dirac impulse input to the circuit was simulated, and time domain features of the output response were classified by a system of two multi-layer perceptrons to produce accurate numerical fault values.

4. FAULT DIAGNOSIS VIA FUZZY LOGIC

Since Zadeh (1965) introduced the theory of the fuzzy sets – manipulating data that were not precise, but rather "fuzzy" and since the work of Mamdani (1974), industrial application studies using fuzzy logic controllers have reached a major position in systems engineering.

Fuzzy Systems are useful in any situation in which the measurements taken are imprecise or their interpretation depends strongly on the context or on human opinion.

4.1 Application studies

Application areas include: the process industry, electromechanical systems, traffic and avionics control and biomedical systems etc.

Evsukoff *et al* (2000) proposed a decision support system dedicated to fault detection and isolation from a human-machine co-operation point of view. Yang & Liao (1999) proposed an adaptive fuzzy system for incipient fault recognition through an evolution enhanced design approach. Complying with the practical gas records and associated fault causes as much as possible, a fuzzy reasoning algorithm is presented to establish a preliminary fuzzy diagnosis system. In this system, an evolutionary optimisation algorithm is further relied on to fine-tune the membership functions of the if-then inference rules. Lu *et al* (1998) described a fuzzy diagnostic model that contains a fast fuzzy rule generation algorithm and a priority rule based inference engine. Insfran *et al* (1999) proposed an approach for fault diagnosis, using fuzzy sets. The system allows not only the fault location, but identification of the fault type. Currents and voltages are analysed using the fault phase-impedance and fuzzy sets. Dexter & Benouarets used a set of fuzzy reference models which describe faulty and fault-free operation, and a classifier based on fuzzy matching for fault diagnosis. The reference models are obtained off-line from simulation data. A fuzzy model which describes the actual plant behaviour is identified on-line from normal operating data and compared with each of the reference models. Mechefske (1998) applied fuzzy logic techniques to classify frequency spectra representing various rolling element bearing faults. The frequency spectra representing a number of different fault conditions are processed using a variety of fuzzy set shapes.

Although fuzzy systems theory is often applied to industrial process, the applications often do not work well. Sometimes fuzzy logic designs are completed without mathematical rigour. The main tasks of finding appropriate membership functions and fuzzy rules are often determined simply by "trial and error". The rules can be obtained by means of optimisation methods. LMI optimisation has been used in order to design an optimal Takagi-Sugeno (T-S) observer based on a relaxed stability condition (Patton *et al.*, 1998). Another main approach to obtain the number, position and type of rules is to apply adaptive and learning algorithms to fuzzy systems or to apply neural networks to learn the parameters of the fuzzy system.

4.2 *Fuzzy Decision-Making*

The advantage of the fuzzy approach is that it supports, in a natural way, the direct integration of the human operator into the fault detection and supervision process. By avoiding an incorrect decision that can cause false alarms the aim of the FDI decision making (for fault diagnosis) is to decide whether and where the fault in the system has occurred (Kuipel & Frank (1997). Fuzzy decision-making objectives are very similar to *expert systems* and supervisory control. Expert Systems are used to simulate the problem-solving and decision-making processes of a human expert within a relatively narrow domain. This is done using special computer packages along with knowledge, information and databases (Ford, 1991; Tzafestas, 1989).

Formulation of decision-making

A decision can be formulated by a set of variables (sets, relations and functions) termed a quintuple **(S, st, C, m, dc)** (Verbruggen *et al.*, 1999; Kaymak,1998). By using available information **S** is the possible actions where a selection of this set is performed. **St** are the set of uncontrolled variables by the decision maker cannot of the environment but they must be included in the decision making process. **C** is the set of consequences, which must be including into a multi-criteria decision-making scheme. Uncertainties resulting from the identification procedure and inherent uncertainties of the system are included, in part, in the consequences. **M** is the relation used to obtain the decision-making solutions by mapping the space **S** x **st** into the set consequences as **S** x **st** $\rightarrow$ **C**. The decision-maker has, *a priori*, aims and objectives in a preference ordering. They are taken into account in **dc** as a decision function **dc: C** $\rightarrow \Re$.

A number of fuzzy decision-making methods for control have been applied for more than 2 decades. For example, the formulation by Bellman and Zadeh (1970). For this approach, there is no distinction between aims and constraints; both are included in the membership functions.

4.3 *Fuzzy Clustering and Fuzzy Identification*

To identify complex non-linear systems it is common to obtain partitions of the available data, each partition or subset is approximated by a simple model. The data can be quantitative or qualitative information or a mixture of both. Clustering algorithms are not only used for classification and pattern recognition to construct fuzzy models but also for the simplification and optimisation in modelling.

Isoc (1998a, 1998b) used quasi-linear fuzzy models based on the Sugeno approach (from experimental measurement data according **to** the Box-Jenkins data sets). These were compared with the real system data sets and then with models obtained using other identification techniques. Various identification techniques to develop fuzzy models were used: for example Mendel-Wang fuzzy reference sets (Wang & Mendel, 1992) were used. The results obtained were of good quality because a more natural inter-dependence between the data set and extracted fuzzy sets was defined.

The fuzzy approach is becoming a powerful alternative to using artificial expert systems and may gain more practical importance in the future. The non-linear system can be identified using a fuzzy multiple-model description of the real system in parallel and a series model or any combination (series-parallel) (Ballé *et al.*, 1997) and consequently a number of models are identified. Lopez-Toribio *et al* (1999) used a different approach. The identification of locally linear models using the Takagi-Sugeno (TS) fuzzy modelling strategy is solved using a convex optimisation technique involving linear matrix inequalities (LMI) in order to find the optimum set of fuzzy models (*Ai, Bi, Ci, Di, for I=1,r*). This approach has been successfully applied to a real-time induction motor drive test rig.

The issue that remains a challenge is to obtain not only a number of multiple linear models but also the minimum number of models, which describe the non-linear system. This optimisation is difficult because the identification method using fuzzy logic depends on a large number of variables. There are various procedures to try to extract learning rules in combination with other techniques (e.g. using neural networks) (Füssel, 1997).

4.4 *Fuzzy Techniques in FDI*

In recent years the application of fuzzy logic to model-based fault diagnosis approaches has gained increasing attention in both fundamental research and application. *Symptoms* can be generated using observers based on the estimation of the output from the system. The first methods used fuzzy set theory to express cause-effect relations in expert systems. The key idea of model-based methods is the generation of signals, termed *residuals*. These are usually generated using mathematical methods (based on state observers, parameter estimation or parity equations). The models correspond to the monitored system (Chen & Patton, 1999). Residuals are signals representing inconsistencies between the model and the actual system being monitored, but the deviation between the model and the plant is influenced not only by the presence of the fault but also modelling uncertainty. One solution is for the observer and controller parameters to be tuned via estimation from the real system for fault isolation and threshold adaptation (Schneider & Frank, 1994). The introduction of fuzzy logic can improve the decision-making, and in turn will provide reliable and sufficient FDI, suitable for real industrial applications. However, difficulties arise in the training of the algorithm in the inference mechanism where knowledge is hidden in large amounts of data and knowledge is embedded in trained neural networks (Chen *et al.*, 1997). A fuzzy feed-forward neural network (FNN) is applied to extract rules from an existing data base. Frank *et al.* (Frank & Kuipel, 1993; Frank 1993; Frank 1994a; Frank 1996; Schneider & Frank, 1996; Frank & Köppen-Seliger 1997) use fuzzy logic for residual evaluation. This can be an important way of taking into account modelling uncertainty at decision-making rather than during residual generator design. By applying a fuzzy rule-based approach the fault decision process can be made robust to the uncertainties so that false and missed alarm rates can be minimised.

Considering *supervisory control* (Linkens *et al.*, 1993, Frank & Kuipel, 1993) with tasks such as system management, process monitoring, identification, fault detection, diagnosis and adaptive capability reduces at lower level the models for developing simpler structures for observers and controllers using TS fuzzy models.

5. INTEGRATION OF QUALITATIVE ANDQUANTATIVE FDI METHODS

Recent research has focused on the integration of symbolic and quantitative knowledge through a neuro-fuzzy system. The aim is to combine the neural network learning ability with the explicit knowledge representation of fuzzy-logic. The application engineer can therefore extract, from the data, a high level language description of the system. Heuristic plant knowledge can also be included.

Some other tools like evolutionary algorithms, genetic algorithms or probabilistic reasoning can also be combined with the above, to enhance the parameter tuning or to deal with the uncertainty in order to establish the desired intelligent system.

5.1 *Combining Neural Networks with Fuzzy Logic*

There are several possible methods of combining neural networks with the fuzzy logic, the advantages and disadvantages of which depend on the specific application.

Farag *et al.* (1998) proposed a five layer fuzzy neural network (Fig. 3) in which the parameter identification of the fuzzy model comprises three phases. In the first phase, initial parameters are found using the Kohonen self- organising feature map algorithm. The second phase consists of finding the linguistic rules. In the third phase, a genetic algorithm known as "multi-resolutional dynamic genetic agorithm (MRD-GA) is used to tune the membership functions.

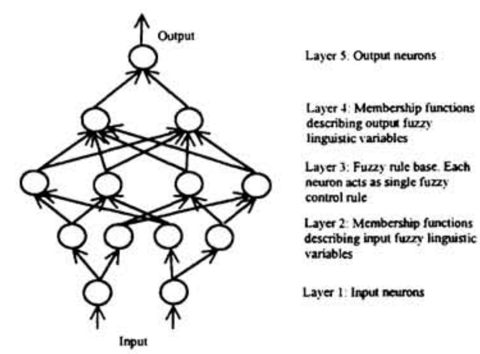

Fig. 3 Fuzzy Neural Networks (Farag *et al.*, 1998)

Li & Elbestawi (1996), proposed a *multiple principal component* (MPC) fuzzy neural network for *clustering* (unsupervised classification) which employs fuzzification of the interconnections of a conventional neural network. This method is used for automated tool condition monitoring in machining and is based on Li and Elbestawi's fuzzy neural networks (Fig. 4) in which fuzzy membership functions are used for decision making and the interconnection in the network.

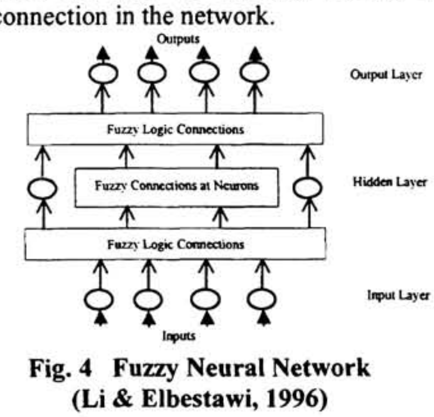

Fig. 4 Fuzzy Neural Network (Li & Elbestawi, 1996)

Altug *et al* (1999) presented two neural fuzzy (NN/FZ) inference systems, namely, Fuzzy Adaptive Learning Control/Decision Network (FALCON) and Adaptive Network Based Fuzzy Inference System (ANFIS), with applications to induction motor fault detection/diagnosis problems. Aggarwal *et al* (1999) addressed the problems of fault diagnosis in complex multi-circuit transmission systems, in particular those arising due to mutual coupling between the two parallel circuits under different fault conditions. The problems are compounded by the fact that this mutual coupling is highly variable in nature. In this respect, the soft computing provides the ability to classify the abnormal phase/phases by identifying different patterns of the associated voltages and currents. A Fuzzy ARTmap (Adaptive Resonance Theory) neural network is employed and is found to be well-suited for solving the complex fault classification problem under various system and fault conditions. Jota *et al* (1998) proposed a combinatorial intelligent system based on neuro-fuzzy, neuro-expert and fuzzy-expert algorithms can be successfully applied in the detection of a number of faults in a range of equipments. Pfeufer & Ayoubi (1997) applied a neuro-fuzzy-structure to the classification of faults, based on symptoms generated by identifying a mathematical model. Ozyurt & Kandel (1996) presented a hybrid diagnostic methodology for fault diagnosis based on a hierarchical multi-layer perceptron-elliptical neural network structure and a fuzzy expert system. The introduced hybrid system is noise tolerant, easy to train and maintain and also reliable under changing process conditions.

Some recent research focuses on neural networks, for example B-spline neural networks, which can be used to extract the qualitative knowledge of the system. The B-spline network is used to classify faults in the process (Patton *et al* 1999). The faults are assumed to be *a priori* known, and their corresponding data available to the designer. The network will then have as many outputs as classes of behaviour (Fig 5). 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 faults as well as that corresponding to the *Healthy* one. This method offers the extraction of fuzzy rules in addition to FDI.

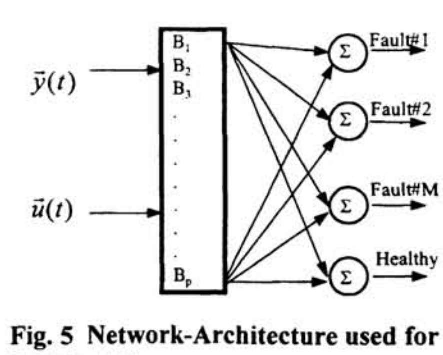

Fig. 5 Network-Architecture used for fault-isolation

As outlined earlier, there are many applications for neuro-fuzzy based FDI. However, successful implementation of neuro-fuzzy FDI methods depends heavily on prior knowledge of the system and the training data.

6. NON-LINEAR FDI VIA FUZZY OBSERVERS

6.1 *Takagi and Sugeno Fuzzy Models: A connection...*

It is possible to establish the equivalence of a generalised class of Gaussian RBF's networks and the Takagi-Sugeno model of fuzzy inference. A standard Gaussian RBF and a restricted form of the T-S model of fuzzy inference are functionally equivalent (Jang & Sun, 1993). The standard RBF network is functionally equivalent to the T-S fuzzy inference model of fuzzy under the following conditions:

First: there are some conditions required to make RBF and fuzzy inference system structurally equivalent like the number of RBF units must be equal to number of *if-then* rules, the T-norm has to be the operator used to compute each rule's firing is *multiplication* and the method to derive their overal outputs for the RBF network should be the same method for the T-S model.

Second: In order to restrict the network to the class of TS structure some conditions must be satisfied: The output of each fuzzy if-then rule is a constant and the membership functions chosen have to be the Gaussian with the same width.

For the Takagi-Sugeno models, the stability conditions and pole assignment in LMI regions are derived in Lopez, Patton & Daley (1999). For a non-linear dynamic system described by the T-S fuzzy model, a fuzzy observer can be designed to estimate the system state vector. For the fuzzy observer design, it is assumed that the fuzzy system model is locally observable, i.e., all (A_I, C_I) (I = 1, ..., r) pairs are observable. Using the idea of *parallel distributed compensation* (PDC) – the use of parallel dissimilar feedback paths, with each on corresponding to a different model – (Wang *et al*, 1995 & Tanaka *et al*, 1996), for a non-linear dynamic system represented by T-S fuzzy model, a linear time-invariant observer can be associated with a fuzzy set M_l for each rule (I = 1, r) of the fuzzy model.

Continuous System:

if $\omega(t)$ is M_l **then**

$$\left.\begin{aligned}\dot{\hat{x}}(t) &= A_i\hat{x}(t) + B_i u(t) + L_i(y(t) - \hat{y}(t))\\ \hat{y}(t) &= C_i\hat{x}(t)\end{aligned}\right\} \quad (4)$$

The overall observer dynamics will then be a weighted sum of individual linear observers.

$$\left.\begin{aligned}\dot{\hat{x}} &= \sum_{i=1}^{r}\mu_i(\omega)[A_i x + B_i u + L_i(y - \hat{y})]\\ \hat{y} &= \sum_{i=1}^{r}\mu_i(\omega)C_i\hat{x}\end{aligned}\right\} \quad (5)$$

$\mu_i(w(t))$ is the grade of membership of the premise variable, $\omega(t)$, or the tensor product of grade of memberships, if $\omega(t)$ is a vector. The membership grade function $\mu_i(\omega(t))$ satisfies the following constraints

$$\sum_{i=1}^{r}\mu_i(\omega(t)) = 1$$

$$0 \le \mu_i(\omega(t)) \le 1 \quad \forall i = 1,2,\ldots,r$$

The schematic diagram of such an observer can be seen as a fuzzy inference engine used to "select" the appropriate output, from those generated by the *r* parallel observers. The transition between one model to the other depends on the operating regime defined by ω.

6.2 *Qualitative fault diagnosis*

Fault diagnosis of dynamic systems can also be based upon declarative knowledge of the system, which is available in qualitative rather than quantitative form (Leitch 1993; Shen & Leitch, 1993; Howell, 1994; Zhuang & Frank 1997). The qualitative approach is based upon the concept of a qualitative model described by means of fuzzy rules which unlike the quantitative counterpart only require declarative (heuristic) information. A fuzzy qualitative observer (Zhuang *et al.,* 1997) can be designed (see Fig. 6) making use of the fuzzy qualitative simulation in order to produce a residual generator. The qualitative model of the process can be seen as an observer. Since the model used to obtain the observations of the process is qualitative, the states (behaviours) will be qualitative. The qualitative states are obtained via simulation or via observation.

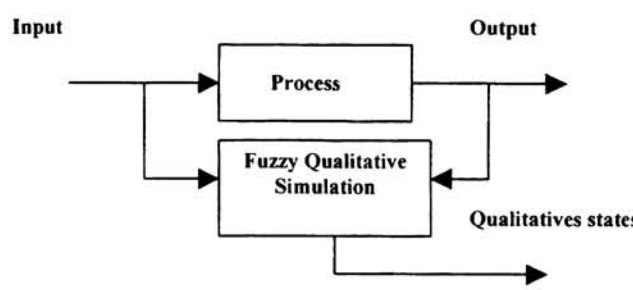

Fig. 6 Fuzzy Qualitative Observer

In order to reduce the ambiguity resulting from qualitative simulation, qualitative observers are used to generate the predictions of the possible qualitative states. In FDI, the qualitative observer can be used as a substitute when not all the quantitative information of the process is available. A Fuzzy Qualitative Simulator developed by Heriot-Watt University, Edinburgh, called *FuSim* (fuzzy interval-based simulator) was proposed by Shen *et al* (1993). This simulator presents a methodology to integrate knowledge of the common sense and the qualitative simulation of physical systems by means of the use of fuzzy sets. The use of an amount of fuzzy space facilitates allows a detailed description of the relations between two or more variables. This method produces a reduction of the set of spurious behaviours by means of temporary filters, although these behaviours continue to exist for complex systems. Like Q2, FuSim uses Taylor-Lagrange formula for the temporary calculations, producing identical problems.

6.3 *Evolutionary Algorithms of Genetic Type*

Neural networks can be trained to replicate dynamic system behaviour during normal and abnormal operation. The neural network behaves as an *implicit* model of the process (implicit - because a mathematical model of the process is not actually required). In order to assure a good accuracy of these models, the neural network structures must be optimised. The research has shown that evolutionary techniques cope efficiently with this optimisation problem. They can be used in order to implement semi-automatic procedures, dedicated to the selection of convenient neural network topologies and parameters. Many papers have focused on the development of evolutionary-based algorithms for two types of neural network structure. The first is applied to a feed-forward network structure and the second is applied to the dynamic multi-layer perceptron. "Near-optimal" neural network topologies can be obtained, by minimising their complexity order and the corresponding output-squared-error computed for the whole training data set. The proposed procedures are used for an appropriate construction of neural observer schemes, in order to perform a robust diagnosis (detection and fault isolation) of the process faults. The user must set some parameters of a genetic algorithm (GA), but this seems to be easier than manually selecting the neural network topology or of using destructive or constructive algorithms. An advanced study of network optimisation using evolutionary programming and GA approaches has recently been reported (Obuchowicz & Patan 1997, Obuchowicz & Korbicz, 1998).

Genetic algorithms have also been used successfully to optimise the design of model-based observers for residual generation (Patton, Chen & Liu, 1997). This study used a multi-objective approach with objectives corresponding to various sensitivity and robustness design issues to achieve good residual response to faults and minimise the effects of disturbance and noise acting at different frequencies. This approach can be contrasted with the use of GA's for neural network optimisation. Zhou *et al* (2000) developed a method of fault diagnosis, based on genetic algorithms (GAs) to resolve this problem. his NPP fault diagnosis method combines GAs and classical probability with an expert knowledge base. Wen & Han (1996) presented a method to fault section estimation using the genetic algorithms in power systems by using the time sequence information of tripped circuit breakers.

7. CONCLUSION

AI approaches to fault diagnosis can be very effective in enhancing the powerful detection and isolation capabilities of quantitative model-based methods. This paper has focused on a discussion of the integration of qualitative and quantitative strategies to minimise the probability of false-alarms and missed-alarms in fault decision-making, whilst improving the level of heuristic information available for the human operator. Residual-based methods for FDI most often use state observers, Kalman filters but there is a growing tendency to substitute the use of the model-based observer/estimator by a neural network, which needs no explicit model for construction and training. The neural network is, on the other hand an implicit or "black box" model which does not give simple insight into the sort of system behaviour which is important for diagnosis.

The main emphasis of the paper has been the simple point that by combining together a fuzzy rule-based strategy with a neural network some powerful diagnostic results can be obtained. This is especially true when considering the diagnosis of complex systems, which are hard to model (e.g. the sugar factory evaporisation plant). The advantage of using fuzzy logic is that it supports, in a natural way, the direct integration of the human operator into the fault detection and supervision process using rules which are easy to understand. Fuzzy logic methods are rapidly becoming a powerful alternative to the use of artificial expert systems.

The combination of neural networks and fuzzy logic for the purpose of fault diagnosis is nothing other than the integration of quantitative and qualitative methods. The so-called fuzzy neural network (FNN) takes the advantages of neural networks in adaptation of knowledge learning, distributed parallel processing of data, associative memory and distributed storage of diagnosis rules, to overcome the difficulties of expert systems in knowledge acquisition bottleneck and knowledge inference matching conflict. The FNN also takes the advantage of fuzzy logic in knowledge fuzzy reasoning to overcome (at least in part) the black box limitation of the neural network.

Several approaches to the FNN have been outlined and the paper has provided a limited survey of some world-wide studies. Of key importance in the literature is the use of the Mendel-Wang and B-spline networks, both of which provide powerful FNN structures for diagnostic reasoning. Some useful results of the application of B-spline networks for modelling and diagnosis of the evaporisation plant of a sugar factory have also been outlined, as a real system example. Part of this research has been funded by an EC INCO-Copernicus project IQ^{2}FD (the Integration of Qualitative and Quantitative Methods for Fault Diagnosis) in which the 11 partners groups have developed, compared and contrasted various methods of integrating qualitative

and quantitative methods for FDI, with a focus on the use of data from the sugar factory.

Finally, the Takagi-Sugeno approach to multiple-model observer design for FDI has been outlined. This incorporates fuzzy rules, based on easily understood premise variables, with state space models dependent on point of operation. This powerful combination of fuzzy logic and quantitative modelling provides a robust solution for FDI, minimising false-alarms and missed detection of faults, in the presence of disturbance and changes in plant operation.

8. ACKNOWLEDGEMENTS

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