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Fault Detection and Isolation (Fdi) Via Neural Networks

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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 used. 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. This main difficulty can be overcome using qualitative modeling or rule-based inference methods. The paper presents the properties of several methods of combining quantitative and qualitative system information and their practical value for fault diagnosis of Neural network. Keywords: Soft computing methods, fault-diagnosis, FDI

I. 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. Configuration used by Chen & Patton (1999) involved a ulti-layer feed forward network configuration (Fig. 1).

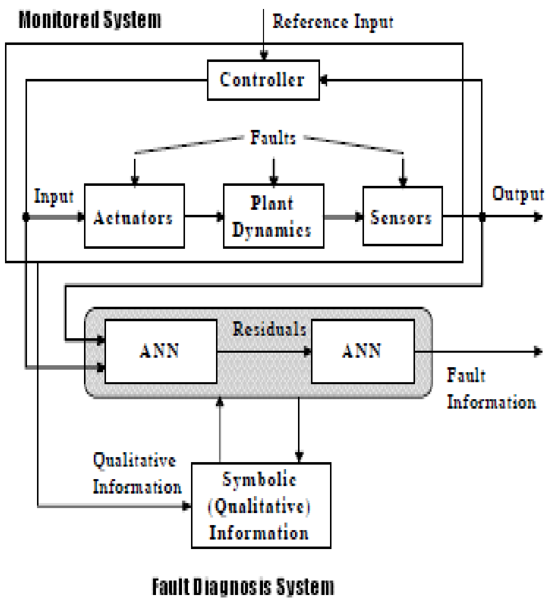

Fig. 1 Neural networks scheme for FDI

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 modeling 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 *generalize* 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 *etal.*, 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-organizing feature map (KFM) to predictive maintenance or condition-based maintenance of electrical drives, particularly induction motors. The first method utilizes supervised learning and in the second the learning is unsupervised.

Application Studies

Neural networks have been successfully applied to many **applications** including fault diagnosis of nonlinear 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 *etal.* (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 behavior 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.

II. 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 the first stage the residual vector **r** is determined in order to characterize each fault. Ideally, the neural network models identify all classes of system behavior. 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 *etal* 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:

$$\dot{X}(t) = A(\theta(t))X(t) + B(\theta(t))U(t) + \xi(t) \qquad (2)$$

$$Y(t) = C(\theta(t))X(t) + D(\theta(t))U(t) + \eta(t) \qquad (1)$$

or

$$Y(t) = H\begin{pmatrix} \frac{d^{(n)}Y}{dt^n}, \frac{d^{(n-1)}Y}{dt^{n-1}}, \ldots, \frac{dY}{dt}, \\ \frac{d^{(m)}Y}{dt^m}, \frac{d^{(m-1)}Y}{dt^{m-1}}, \ldots, U \end{pmatrix}\theta(t) + \varepsilon(t) \qquad (3) \quad (2)$$

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.

III. 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 preclassifier 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 optimize 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.

IV. Design issues of applying neural

Networks for fault diagnosis 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 behavior (from an input-output point of view). This does not enable the user to understand the system and predict its behavior 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 generalize well when presented with data outside the training I/O space. MLP and Fuzzy Logic based systems on the other hand tend to generalize 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.

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 normalization as pre-processors. The proposed system has the capability to detect and identify faulty components in an analog electronic circuit by analyzing 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 wave net 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.

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 nresponse 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.

Robust fault detection: The model based FDI should represent signals which reflect the inconsistence between deviations from normal to fault detected systems. The uncertainty of the model could reduce the reliability of fault detection when it is not considered. There are two approaches active and passive based on robust observation and adaptive threshold computed for the residual. If the threshold chosen is too small, uncertainty cause false signal otherwise small faults cannot be

Detected, when threshold is chosen to the time evolution of the residual [J.Korbicz et.al, 2004] In the fault free case. Fig.2 shows the idea of threshold adaptations and it is clear from figure that if a fixed threshold is use (dash lines) then the false signal occurs at the time T_{fa} and the fault at T_f cannot be detected. When adaptive threshold is used the residual caused by the input in fault free case, the false $r[k] = y[k] - \bar{y}[k]$ signal can be avoided and fault at T_f be detected.

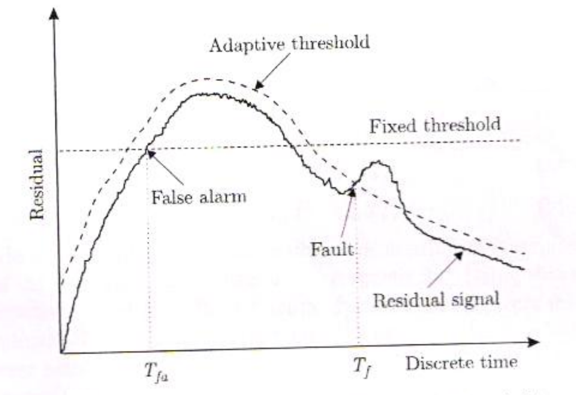

Fig. 2. Illustration of the concept of the adaptive threshold

V. 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 minimize 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 behavior which is important for diagnosis.

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