PREFACE

This special issue is concerned with the presentation of new ideas and results developed under funding support from a EC INCO-Copernicus project IQ^{2}FD (Integration of Qualitative and Quantitative Methods for Fault Diagnosis). The aim of the project has been to develop mechanisms for integrating new quantitative and qualitative methods within the framework of industrial applications.

It is sometimes necessary to control a complex system when there are faults present or when the system undergoes set-point changes (perhaps due to unknown parameter variations). To keep the function of closed-loop control, during small faults and system changes, it is necessary to generate information about these changes for a supervision scheme. The role of supervision in such a system is to assess the severity of faults/system changes and schedule a suitable feedback control action to maintain closed-loop system performance. It is important to be able to detect and isolate faults/changes before they have drastic effect on system performance.

An important way to detect and isolate such small, early or *incipient* (hard to detect) faults is to use techniques based on quantitative models of system input-output dynamic behaviour. Model-based estimator schemes are used to generate "residual" signals corresponding (in simple terms) to the difference between measured and estimated variables. The residuals are processed using either deterministic (e.g. using fixed or variable thresholds) or stochastic techniques (based upon decision theory — likelihood ratio testing, etc.). Once a fault/change is detected using these methods, further procedures (e.g. structured or directional residuals or probability methods) must be used to isolate each fault.

Estimators used for residual generation can take several possible forms, e.g. full or generalised observers, parameter estimators, parity equation schemes or stochastic approaches — based principally on Kalman filters. All of these use *quantitative models* of the process being monitored. Whilst most are based on the use of linear models, non-linear extensions are also available (e.g. non-linear observers, extended observers, extended Kalman filters, etc.). Unfortunately, for many process systems, quantitative model information is not always readily available. Quantitative models can be hard to obtain or the plant behaviour is too complex to be described using linear models.

An alternative to the use of quantitative modelling for Fault Detection and Isolation (FDI) can be based on the idea that system variables also have "qualitative characteristics" (e.g. increase, decrease, change in slope, slow change, fast change, low, medium, high, etc.). Using this notion, qualitative system models can be developed and used in a very powerful way to augment or (in some cases) replace the use of quantitative model information.

In this INCO-Copernicus project we have developed several strategies for combining quantitative and qualitative model information for FDI, keeping in mind the need to apply our methods to real industrial processes. Every real system application has important inherent qualitative information which cannot always be extracted from a quantitative model. A suitable combination of qualitative and quantitative model information can provide a powerful framework for reliable diagnosis and supervision of complex systems.

In the first overview paper Patton *et al.* discuss recent approaches to FDI for dynamic systems using methods of integrating quantitative and qualitative model information based upon Artificial Intelligence (AI) techniques. The use of AI methods (neural networks, fuzzy logic, expert systems) is considered as important extension to the quantitative model-based approach for residual generation in FDI. The properties of several methods of combining quantitative and qualitative system information and their practical value for fault diagnosis of real process systems are discussed.

Artificial neural networks (ANNs) are easy to train with measured input and output data from a plant. Once trained they can be used to represent the input-output behaviour of the dynamic system and as such behave as a model of that system. The disadvantage is that, although quantitative, this is an *implicit model* which means that the dynamic behaviour is not easily describable in terms of the more usually understood methods of differential equations, transfer functions, etc. To diagnose a system using a quantitative model-based approach, we really need to use *perfect explicit models*, for which there are no model uncertainties and the plant behaviour is completely described. Clearly, such a perfect model does not exist and neural networks can still fulfil an important modelling role, particularly in situations when explicit models are difficult or impossible to obtain. Four of the papers of this special issue are concerned directly with the use of neural networks for the FDI function.

Korbicz *et al.* describe the use of multiple-model strategies for representing a plant's dynamic behaviour at different operating points. They use dynamic neural networks to generate residual signals for the purpose of detecting and isolating faults. To improve the quality of neural modelling, two optimization problems are included in the construction of such dynamic networks: searching for an optimal network architecture and the network training algorithm. The effectiveness of this neural dynamic network approach is demonstrated by applying it to modelling Narendra's system and the two-tank system fault diagnosis.

Marcu *et al.* also use dynamic neural networks for developing neural observer schemes. Three types of generalised dynamic neural networks are properly integrated in order to obtain the best approximation of process outputs for known classes of the system behaviour. The passive robustness of the diagnosis subsystem in ensured, in the stage of decision-making, by means of static ANNs. They are used as pattern classifiers that evaluate symptoms generated by neural observers. Component fault diagnosis and instrument fault diagnosis of a three-tank system are presented in a comparative study.

Szabó and Horváth deal with a family of CMAC-type neural networks and their applications for efficient modelling of static and dynamic systems. They give a critical review of the classical binary CMAC and suggest some modifications. The aim of these modifications is to improve the modelling capability of the network and at the same time to maintain its fast training and ease of implementation. For this purpose, the use of discrete higher-order basis functions and a special multiplier structure have been proposed. Such networks are especially suited for real-time applications in low-cost embedded systems.

Zítek *et al.* address the problem of neural network evaluation of model-based residuals for fault diagnosis of time delay systems. Two methods of fault detection have been proposed for a laboratory-scale heat transfer set-up: functional state observer and a modified internal model control scheme.

Dalton *et al.* use sensitivity theory to analyse a certain class of fuzzy systems which can be used for FDI. The method is applied to a fuzzy fault diagnosis scheme for a two-tank laboratory system. Simulation results for the fuzzy and non-fuzzy fault diagnosis schemes are also presented.

The first paper by Kośćielny *et al.* presents an application of fuzzy logic in a fault isolation scheme. The fuzzy interpretation of residuals allows for taking into account the main uncertainty occurring in the process of decision-making. The proposed so-called F-DTS method of diagnostic reasoning is adopted for diagnosing complex systems.

The next paper by Kośćielny *et al.* discusses an idea of decomposing the diagnostic tasks in complex systems. The decomposition consists of splitting diagnostic functions into lower-level units and supervision of the process. The fuzzy identification algorithm proposed ensures robustness to measurement disturbances and can be easily implemented in a microprocessor-based positioner. The tests performed were the initial phase for the implementation of their approach in an industrial MERA-PNEFAL positioner.

Calado and Sá da Costa discuss an on-line FDI system designed to be robust to the normal transient behaviour of the process. The system consists of an expert system in cascade with a hierarchical structure of fuzzy neural networks. This structure was designed to allow for the diagnosis of single and multiple simultaneous abrupt and incipient faults. A continuous binary distillation column has been used as a test bed for their FDI scheme.

A multi-objective Pareto-optimization procedure for the design of residual generators in FDI systems is presented by Kowalczuk *et al.* A practical solution to the optimization problem has been found with the use of inequality constraints and genetic algorithms. The effectiveness of the proposed approach is illustrated for the unstable state-space plant model.

In the last paper, Janczak uses Wiener and Hammerstein systems via generation and processing of residual sequences for FDI. Based on a serial-parallel definition of the residual error, new fault detection and isolation methods are proposed. Fast and reliable estimation methods for parameter changes caused by system faults are considered.
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