A NOVEL SOFT COMPUTING APPROACH TO COMPONENT FAULT DETECTION AND ISOLATION OF CNC X-AXIS DRIVE SYSTEM

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ABSTRACT—We propose a novel soft computing (SC) based approach to design fault detection and isolation (FDI) systems for industrial plants, in particular a highly nonlinear CNC X-axis drive system's component fault detection. The aim of this paper is twofold. One is to present a general description of various concepts such as the novel fuzzy-neuro architecture that uses fuzzy clustering to build a nominal model, fuzzy decision-making subsystems, a central processing unit for estimation of fault location, and finally RBF neural networks to estimate fault size. The other aim is to apply proposed method to diagnosis of component faults of a CNC X-axis drive system amid significant noise levels. Simulation results demonstrate the significance of the proposed approach.

Key Words: Fault Detection and Isolation (FDI), Soft Computing (SC), Fuzzy Decision-making Systems, Fuzzy Clustering, CNC X-Axis Drive Systems

1. INTRODUCTION

Fault Detection and Isolation (FDI) is an essential part in intelligent control of industrial plants due to an increasing demand for higher performance as well as higher safety and reliability. The early detection of faults can help avoid system shutdown, breakdown and even catastrophes involving human fatalities and material damage. Different fault detection and isolation techniques began by various researchers in the early 1970's, and various FDI approaches based on analytical redundancy have been reported since then [1]. These different techniques can be categorized to various general approaches such as the parity space approach [2,3], the parameter estimation approach [4,5,6], the state estimation approach [1,4,5] and the fault detection filter approach [7]. Most of the existing model-based schemes use quantitative models to estimate the states, system parameters or outputs of the system in order to generate necessary error signals [8]. A major problem associated with such approaches is that, in practice, it is almost impossible to obtain a model that exactly matches the process behaviour [9]. This is because these techniques are mostly limited to linear systems, and hence do not apply well to nonlinear systems. Consequently, there is an increasing demand for reliable methods of fault detection and diagnosis for non-linear systems,

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particularly for systems with certain unknown non-linear characteristics [10,11]. To address the above nonlinearity problem, the investigation of FDI schemes has, in recent decade, entered into a new era by advances of artificial intelligent concepts such as fuzzy logic (FL), artificial neural networks (ANN) and genetic algorithms (GA). For example, considering the success of fuzzy logic-based real-time control schemes in recent years, it is reasonable to investigate new FDI schemes from the FL perspective. The main and unique advantage of FL systems is to treat system behavior using a set of *if-then* relations using both qualitative and quantitative information, i.e. both knowledge and experience of experts and measured data respectively [12]. Using this property, the rich information of experts (engineers and operators) about system conditions could be incorporated to design the diagnosis systems in the form of a knowledge-based FDI system [13]. The advantages of FDI systems based on FL are considered in [14,15,16]. For instance, fuzzy decision-making systems [17] and fuzzy thresholds [18,19] were used in residual evaluation and also fuzzy rules to either assist or replace the use of a model for diagnosis [20]. Also, different applications have shown the ability of ANNs to design suitable FDI systems in connection with both predictors of dynamic nonlinear models as well as pattern classifiers [12,21,22]. Others used various soft computing concepts, i.e. hybrid combinations of FL, ANN and GA, such as supervised and reinforcement training of ANN by GA or FL for reaching a higher quality of fault identification [11,23, 24]. Smarter and more capable FDI structures can be expected from combining the learning capability of ANN, the transparency and interpretability of fuzzy systems, as well as the optimizing capability of GA [22,25,26,27]. The above mentioned approaches generally either attend to the problem of residual generation or residual evaluation, as will be explained in more details in Section 2. Figure 1 describes the appropriate paradigm of intelligence for each of these soft computing views of FDI.
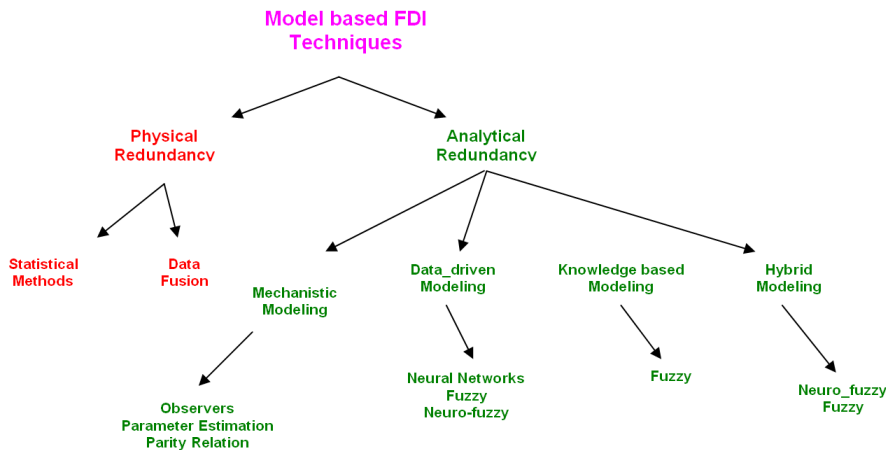

Figure 1. Shows a general classification of different FDI approaches.

We propose to attend to both problems of residual generation and evaluation using a novel soft computing based architecture. In particular, a novel fuzzy-neural FDI architecture is proposed that uses fuzzy clustering concept to build a nominal model, fuzzy decision-making subsystems and a central processing unit for estimation of fault location, and finally RBF neural networks to estimate fault size. The proposed method is then applied to diagnosis of component faults of a CNC X-axis drive system.

2. THE PROPOSED FDI APPROACH

There are basically two viewpoints in design of model-based FDI techniques. One is to generate significant residuals and symptoms that contain rich and satisfactory information about faults as much as possible. The residual evaluation becomes relatively easy if residuals are well designed. The other is to design powerful diagnosis systems using sophisticated techniques, which reflect fault specification and adopt a reliable, safe and optimal decision accordingly, even if the residuals are not well-designed. Normally, the FDI systems based on analytical models, i.e. parity space, state/parameter estimation method, and so on, concentrate on addressing the first viewpoint, and intelligent decision-making systems based on FL, ANNs and GAs address the second viewpoint. In this paper, we demonstrate that a combination of the above two viewpoints can have potentially significant improvement to FDI systems. Namely, in the proposed soft computing based FDI system, because of the successful clustering-based modelling, the residuals regarding specific faults have uniquely recognizable patterns. Consequently the residuals are well-designed, and a robust diagnosis system for residual evaluation can been designed. Figure 2 shows a schematic of the proposed FDI approach.
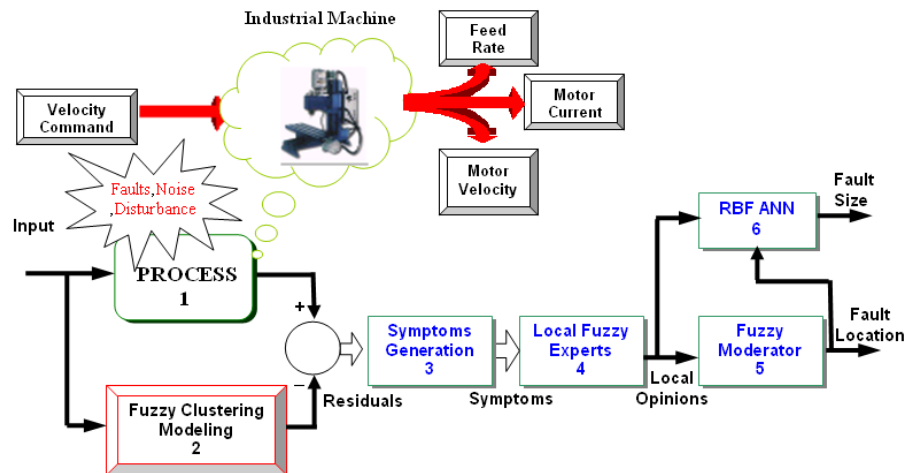
Figure 2. Schematic of proposed FDI structure

The structure is composed of six blocks, with the first block representing the actual system. The second block represents a nominal fault free process model using fuzzy clustering. Residuals are the difference between actual and fault-free signals of system. The third block represents the symptoms generation routine; several specifications of residuals are extracted here. The fourth block represents several primary fuzzy fault location estimators each with expertise only on a certain type of fault. The outcomes of these "local experts" are then processed by a central moderator; and finally, the last block represents the fault size estimation using RBF neural networks. It is important to note that in order to decide which type of AI-based or conventional models have the sufficient approximation properties to use in this research, a number of different soft computing modelling techniques such as in ANNs and FL and conventional modelling techniques such as ARMAX and ARX were considered and tested [28]. There, it was reported that the fuzzy clustering and RBF networks gave the best results in terms of accuracy of prediction and success in learning, i.e. less computational cost while maintaining higher accuracy

[29,30]. In the following section, a general perspective on design of the novel FDI structure is explained.

2.1 Fuzzy Clustering for Design of Nominal Plant Model

The heuristic and nonlinear nature of fuzzy rules and the relationship between fuzzy sets of different shapes are the basis of fuzzy logic's powerful capability for modelling a system whose complexity renders other more traditional approaches difficult to handle, such as conventional expert-based, mathematical, and/or statistical approaches. In general, fuzzy clustering concept consists of two steps. The first step is the fuzzy partitioning of the input pattern space into fuzzy subspaces and second step deals with the determination of the rules and membership functions for each subspace. The performance of this model depends on the choice of the fuzzy partitions. The suggested method does not necessarily require the physical knowledge of the process under observation since the input-output links are obtained by means of an identification scheme which uses a data driven fuzzy modelling scheme. Physical knowledge of the process is used elsewhere in design of fuzzy decision-making subsystems for estimating fault locations, see subsection 2.3. As will be shown, the residuals generated by the fuzzy clustering method are well-behaved. This in turn will simplify both detection and isolation of faults in following stages.

2.2 Residual and Symptom Generation

Residuals are fault indicators, based on deviations between the actual and fault-free (in absence of any fault) signals of system under consideration such as system outputs, state variables, system parameters and/or any of their combination. A useful residual signal is one that exhibits robustness against system uncertainties as well as sensitivity against known faults, two seemingly competing properties. It is very important to note that an adequate and powerful design of the residual generator allows fault isolatability, and consequently classification of the residuals into a specific fault-case. It will be evident that the fuzzy clustering-based nominal model can be successful in satisfying these objectives if the fuzzy fault free model is as accurate as possible. Symptom is a change of an observable quantity in a residual signal. For detection and diagnosis of a fault in a plant under consideration, several distinguished quantities are extracted from any residual as symptom indexes. These quantities are as follows: Maximum, Minimum, Steady state value, number of peaks and start point of any residual.

2.3 Local Fuzzy Experts for Primary Estimation of Fault Location

During fault isolation process, several fuzzy decision making local experts (LE) are used to examine the symptoms. Every one of these local experts provides advice for a specific fault type. A moderator then extracts features from these advice signals, and classifies them appropriately in order to isolate faults reliably. When knowledge about a certain fault type is interpreted as local, a system designer can incorporate his own expertise to adapt/optimize it separately from other expertise about other fault types of the system. In this fashion, if there is any problem with the FDI scheme, such as stability, in a certain situation, the design can simply be adapted or optimized for the same situation without any ill-matched effect to others. In comparison, in traditional control techniques, the most parameters and factors of system have a global effect in system performance. Thus adaptation and optimization of a situation could have had undesirable effect upon other situations. In these cases, optimization problem is a very difficult and interwoven process. Using results from previous processing stages, i.e. residual and symptoms generation blocks, local fuzzy expert systems are designed for primary localization of faults, based on fault tree concept. Each one of the several local experts classifies the patterns of symptoms to perform a primary estimation of the occurrence of a particular fault f_i condition. Finally, using outputs of

these LE subsystems, a fuzzy moderator performs a final yes/no decision on a given fault and indicates its possible state. The outputs of LE subsystems are fault occurrence indexes that have elements with values between 0.5 and 1, with 0.5 meaning neutral state. As soon as one of the elements exceeds 0.5, fault occurrence is indicated. Here, the local expert LE design procedure is described. **Step 1** is gathering data that would help explain the relation between significant quantifiable properties of residuals' symptoms and process conditions. When there is an accurate plant model, accurate and nonlinear fault occurrence conditions can be simulated by disturbing the model parameters. Then, the relation between these disturbances (simulated fault occurrences) and residual symptoms need to be found. In addition to using an accurate plant model, it is also possible to take advantage of experts and plant information bank based on numerical data and expert knowledge. Such simultaneous utilization of plant model, expert's knowledge and plant information bank can enhance the safety and validity of designer's decision. **Step 2** is formulating the above-achieved relations with fuzzy if-then rules. A separate LE subsystem has been used to diagnose every known fault. It should be mentioned that these local decisions will be considered and analyzed by a central fuzzy moderator. **Step 3** is to indicate fuzzy variables with suitable membership function limits. The membership function limits determine the threshold of fault detection, so they are carefully chosen to provide robustness to system uncertainties and yet high sensitivity to the fault occurrence. **Step 4** is to write the fuzzy rules based on above steps. The performance of the LE subsystems is important for estimating the type of the fault with high certainty by the fuzzy moderator.

2.4 Fuzzy Moderator for Declaration of fault Occurrence Situation

A fuzzy moderator decides final yes/no decision on a given fault and indicates its possible location using output of the LE subsystems, numbers between 0.5 (no faulty) and 1 as fault occurrence indexes. The objective of this stage is to discriminate between a healthy system and a faulty system and, if faulty, whether a trained faults or novel faults is occurring as explicit as possible. Also, if it is a trained fault, it decides which fault regarding to output sensors and system components are occurring, but not the size of the fault.

2.5 Fault Size Estimation Unit

In fault size estimation unit, a separate neural estimator has been designed for each fault occurrence condition. These estimator networks have been trained by LE subsystems' output as well as output of the fuzzy moderator.

The required data for training is derived from simulating fault occurrence conditions in plant model or gathering actual data from real plant. Figure 3 shows the hierarchy block diagram of above discussion in which *m* local fuzzy experts and *m* RBF networks analyze type and size of *m* known faults respectively.

3. APPLICATION: CNC DRIVE SYSTEM DESCRIPTION

In this section, a simulation example is used to study performance of the proposed hybrid methodology for a CNC X-axis drive subsystem. The axis drive is the positioning device for the relative movement between the work piece and the cutting tool. The drive system is usually composed of the position controller, servo system and a table or slide mechanism that feeds the workpiece towards the cutter [31]. Many of the parameters of CNC X-axis drive system in nominal (free-fault) condition are already available from the manufacturing handbook [32] but others such as friction coefficients, stiffness and backlash were measured experimentally [31]. Ebrahimi and Martin indicated that identification models of position controller and servo amplifier
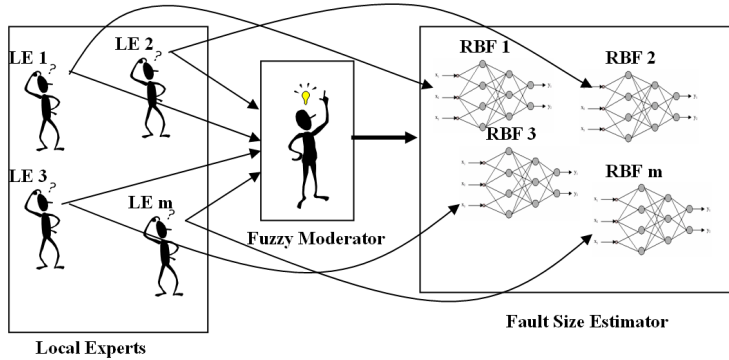
Figure 3. Hierarchy of local expert decision making, fuzzy moderator and RBF networks.

are accurate enough and their model was validated by comparing the model output with the actual output of the system for different sets of realistic inputs [33]. Figure 4 shows a block diagram model of X-axis drive system [33]. Twelve parameters are considered here which could typically cause known fault conditions within the system, consisting of *M, CF, R, B, K_v, K_m, J, B_R, K_2, K_1, BL, and K_x* . Table I shows the nominal parameters of CNC X-axis drive system categorized by type. The input to the X-axis drive system is a controlled voltage. Motor current, motor velocity and feed rate are three outputs of the X-axis drive system. These three outputs are chosen as fault indicators, and residuals are generated by inconsistency between the actual system and the nominal (free-fault) model.

4. DESIGN PROCEDURE

The proposed FDI mechanism consists of simulating a nominal model and symptom generation, a set of fuzzy local experts, a fuzzy moderator, and a set of RBF network for fault size estimation. These stages, implemented in Matlab, will be explained in the following sections.
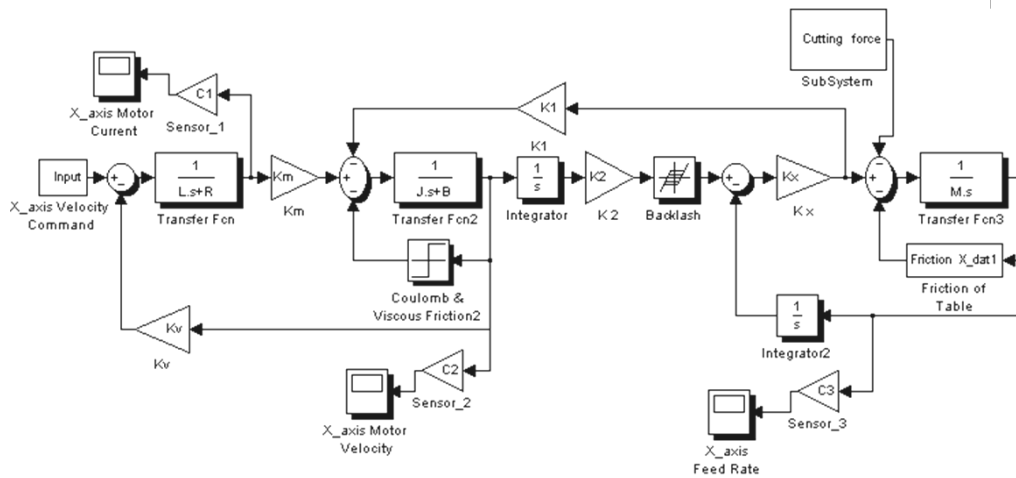

**Figure 4. Block diagram model of X-axis drive system.**

Table I. A listing of fault types, their parameters and symbols.

| PARTS	PARAMETERS	Symbol	Values	Fault Type
TABLE	Mass	M	270	10
	Coulomb friction coefficient	CF	126	12
DC MOTOR	Armature resistance	R	0.33	2
	Armature inductance	L	1.16	1
	Voltage constant	K_v	0.53	4
	Torque constant	K_m	0.53	3
ROTARY PARTS	Inertia	J	0.04	5
	Viscous friction coefficient	B	0.0024	6
	Rotary to linear constant	K_2	0.0016	7
	Force to torque constant	K_1	0.0016	8
	Backlash	BL	0.005	11
	Stiffness	K_x	10^5	9

4.1 Nominal Model

A model based on fuzzy clustering method is used here to estimate the output signals of the nominal process. As reported [28], the resulting fuzzy model of CNC X-axis drive system has negligible modelling error. Considering that the outputs of the nominal model are well designed, i.e. residuals produce similar patterns for size variations of a given fault and significantly different patterns for different faults, it is not necessary to build faulty models bank. Therefore, an appropriate model has been built by fuzzy clustering method when the system is working under healthy condition.

Figures 5, 6 and 7 show the simulated outputs of process under nominal conditions using fuzzy clustering as well as actual signals in a fault-free situation. The figures on the left are the errors in approximation, on the order of 10^{-15}.
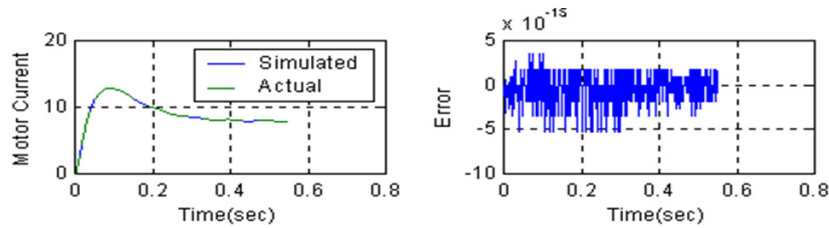
Figure 5. Motor current - actual vs. simulated data (left) and corresponding error (right)
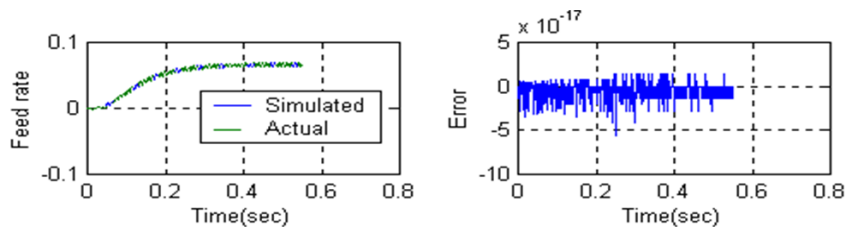
Figure 6. Feed rate - actual vs. simulated data (left) and corresponding error (right)
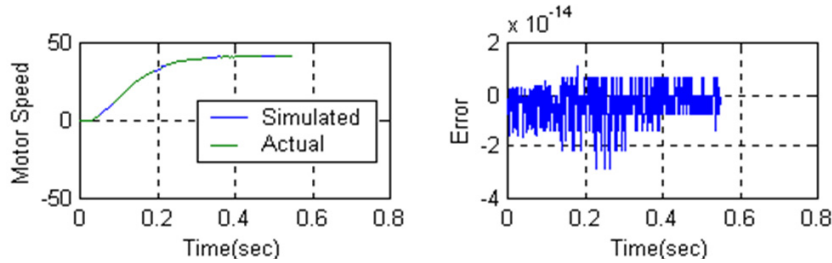
Figure 7. Motor velocity - actual vs. simulated data (left) and corresponding error (right)

4.2 Residual Signals or Symptoms

Figures 8-9 show typical generated residual signals as a result of a component failure. In these figures Re-I, Re-V and Re-FR describe the residual regarding to 1st, 2nd and 3rd output, i.e. motor current, motor velocity and feed rate, respectively.

As can be seen, residuals regarding to changes of a specific parameter have a unique pattern and on the other hand have a different pattern than residuals regarding to other parameter changing. From the simulated results, it is evident that the residuals are corrupted with noise and hence a powerful fuzzy decision system for diagnosis of faults will be necessary. Symptoms such as maximum, minimum, starting point, steady state values and number of peaks are extracted from residuals. In this research, we studied 48 situations: four fault sizes (0.5%, 10%, 50%, 90%) for each of 12 fault types. Due to the number of case studies, only one situation is illustrated here.
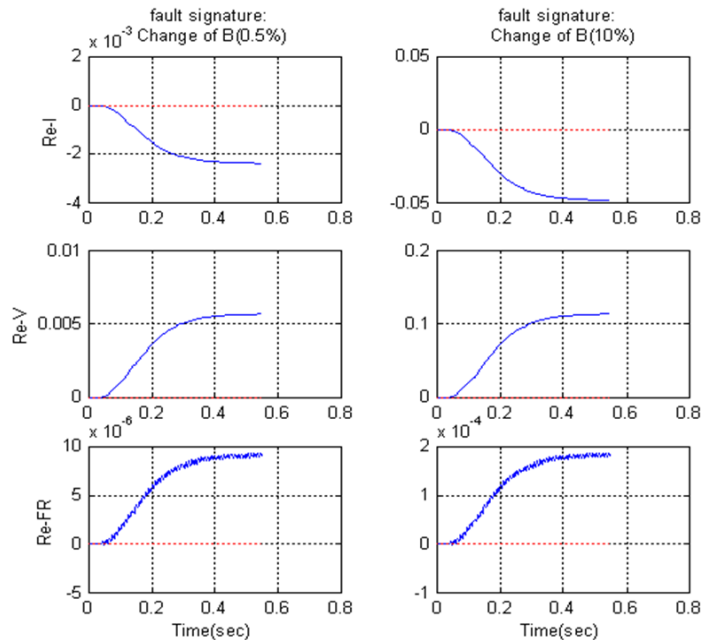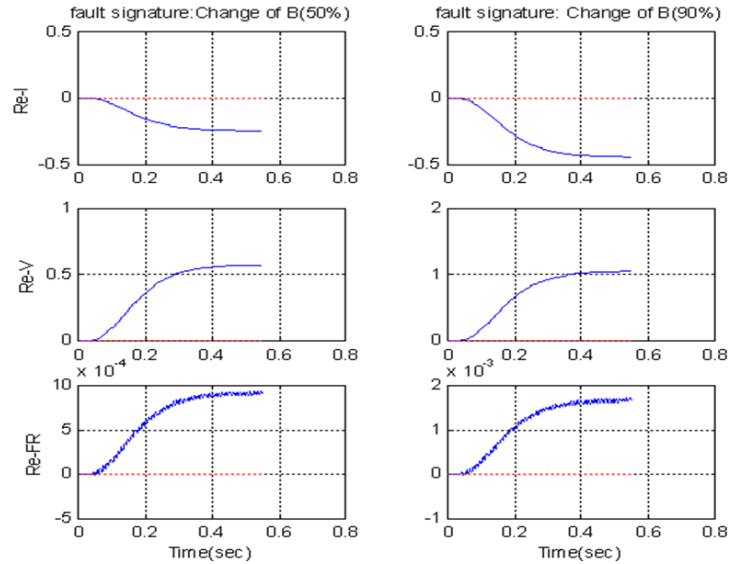

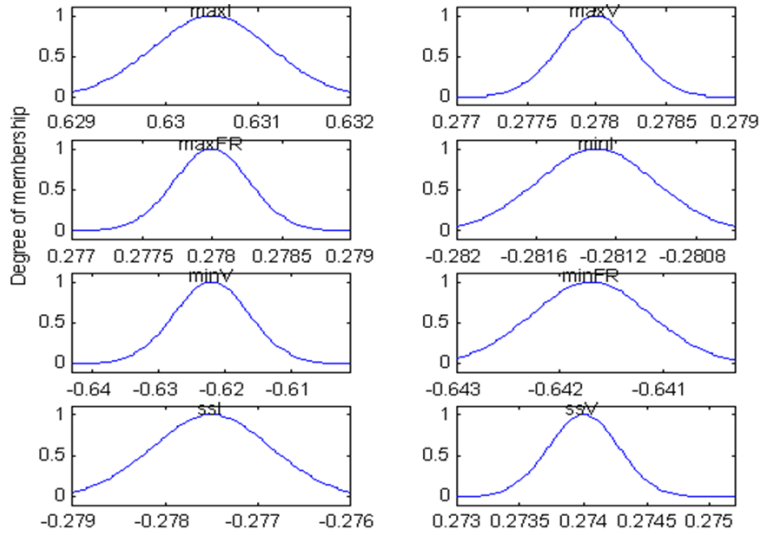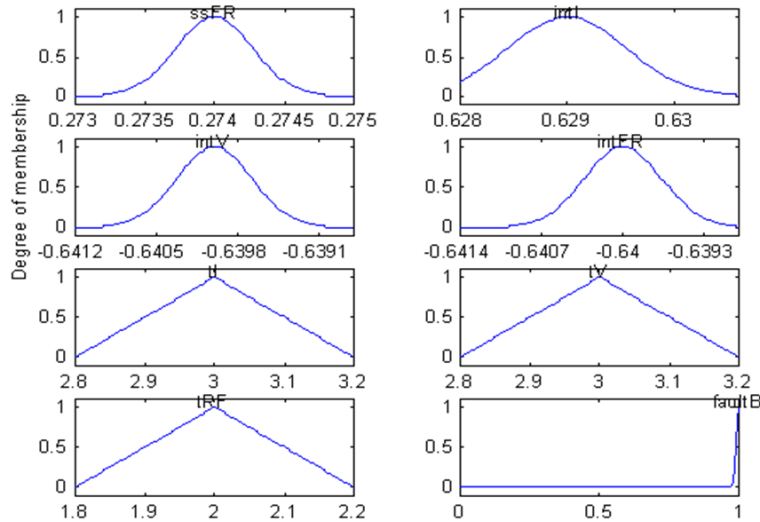**Figure 8. Residual signals of changing of 0.5% and 10% in viscous friction coefficient of rotary part (B)**

Figure 9. Residual signals of changing of 50% and 90% in viscous friction coefficient of rotary part (B)

4.3 Fault Detection and Isolation

Using results from previous sections, i.e. symptom, and fault tree concept or faulty conditions (see subsection 2.3), a suitable decision mechanism has been designed to localize faults based on fuzzy logic. The decision mechanism consists of several fuzzy specialists, each trained and concerned for only one fault condition, and a fuzzy moderator to decide whether a known fault has occurred or not. The fuzzy moderator uses output of these fuzzy specialists to adopt a final yes/no decision on a given fault and to indicate its possible cause. As will be shown, a fuzzy specialist evaluates the pattern of residuals, or symptoms, and uniquely relates them to a particular fault condition [28]. The fuzzy specialist is created first by deciding on appropriate universe of discourse for each of fifteen inputs, i.e. maximum value, minimum value, steady state value, start point value and number of peaks of three residual signals, as well as its output, i.e. fault location index in plant components. Membership functions are assumed normal and of triangular and bell-shaped functions. Figures 10-11 show the typical membership functions of fuzzy subsets of fifteen inputs and one output respectively. The terms of linguistic variable are used to describe the states of the fuzzy specialists as follows: Max(r), min(r), ss(r), int(r) and t(r) which indicate "maximum," "minimum," "steady state," "start point" and "number of peaks" of signals under consideration respectively, and r is any of the three residual signals. For example maxFR indicate maximum value of feed rate residual signal, ssV indicates steady state value of motor velocity residual signal, and also membership functions which is labeled as 'fault-x' is for output of fuzzy specialist, i.e. fault location index in plant components, in which 'x' sign deals with system component. Each fuzzy specialist in the proposed FDI scheme contains one 'if-then' rule. Figures 12-13 show the LE subsystem outputs (primary fault location) regarding to change in B and K_2 respectively.

Figure 10. Membership functions for minimum, maximum and steady state values of residual signal of viscous friction coefficient of rotary part (B)

Figure 11. Membership functions for steady state, start point value, and peak residual signals of viscous friction coefficient of rotary part (B) and also membership functions corresponding to fuzzy decision subsystem output

4.4 Fault Size Estimation

There are separate RBF networks for each of the known (trained) faults; their task is to estimate the size of their corresponding faults. Thus each fault has its own RBF network, and during learning the various simulated sizes of a single fault are fed as teachers. It is important to note that in this procedure, size of faults may approach very accurate in simulation but in practical terms these are not expected because the aim of condition monitoring is to detect faults at an early stage.
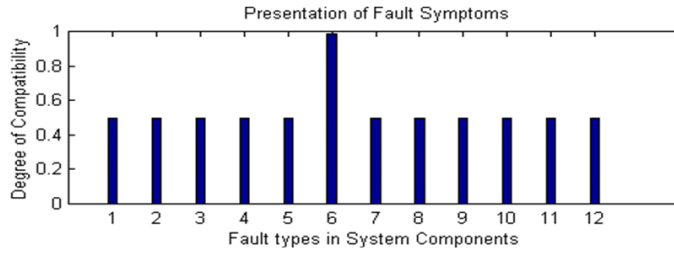
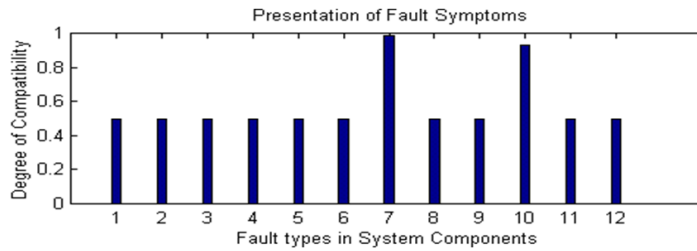**Figure 12. Fuzzy specialist output corresponding to 3% changing of B**

Figure 13. Fuzzy specialist output corresponding to 56% changing of K_2

4.5 Simulation Results

Several toolboxes of MATLAB are used here such as Simulink, Wavelet, Genetic Algorithms, neural networks and fuzzy logic. Figures 14-15 show the FDI system output regarding to 3% changing of B and 56% changing of K2respectively. In the Figures, the numbers from 1 to 12 correspond to the component faults in L, R, Km, Kv, J, B, K2, K1, Kx, M, BL, CF respectively as demonstrated in Table I. The below Figures indicate the final diagnostic system outputs (Fuzzy Moderator and RBF network), i.e. fault size and its location are depicted in two cases studies. The Figures attempt to draw a comparison between actual and estimated fault types and sizes from an operator perspective. Also, a number of incipient and abrupt faults have been considered in this research, but due to brevity few of them are presented here. In total, 400 tests were carried out; the FDI mechanism was able to always locate the fault locations.
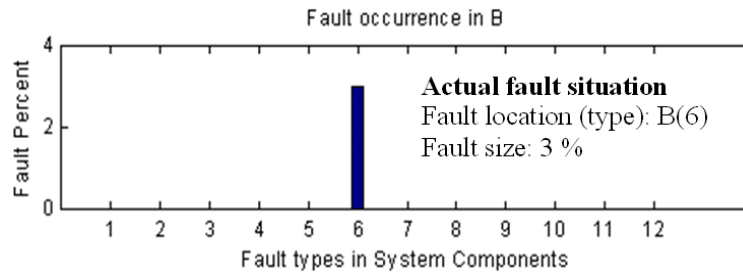

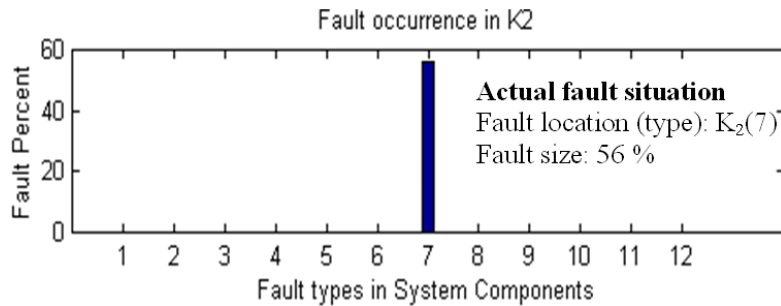**Figure 14. FDI system output corresponding to 3% changing of B**

Figure 15. FDI system output corresponding to 56% changing of K$_2$

5. CONCLUSION

In this paper, a novel intelligent algorithm is presented for fault detection and isolation (FDI) of dynamical systems. Twelve incipient and abrupt faults are detected and diagnosed using a set of proposed symptoms. Several faults in nonlinear parameters were detected which have more significant effect on overall accuracy of plant. Furthermore, RBF networks provide a suitable mechanism for estimating fault size. The fuzzy specialists for localization of faults have a flexible architecture and therefore its adaptation or development is simplified because adaptation of a fuzzy specialist does not influence others greatly. The proposed FDI structure covers the challenging problem in all FDI systems, namely it provides high system sensitivity against occurrence of known faults as well as robustness with respect to noise and disturbance. To utilize the proposed FDI structure, the designer can use either linear, highly nonlinear model of plant or a set of input-output signals of plant; namely this system has abilities of FDI systems based on both qualitative and quantitative models. The minimal detectable fault values in this application (CNC X-axis drive system) are 0.5 percent. Due to system noise, the system was unable to correctly classify faults with less than 0.5% error. The results obtained by this approach indicate that suitable fusion of computationally intelligent techniques and their uses for residual generation as well as residual evaluation is useful for industrial applications such as the CNC drive.

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