SOFT COMPUTING FOR FAULT DIAGNOSIS IN POWER PLANTS

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Abstract

Considering the advancements in the AI technology, there arises a new concept known as *soft computing*. It can be defined as the processing of uncertain information with the AI methods, that refers to explicitly the methods using neural networks, fuzzy logic and evolutionary algorithms. In this respect, soft computing is a new dimension in information processing technology where linguistic information can also be processed in contrast with the classical stochastic and deterministic treatments of data. On one hand it can process uncertain/incomplete information and on the other hand it can deal with non-linearity of large-scale systems where uncertainty is particularly relevant with respect to linguistic information and incompleteness is related to fault tolerance in fault diagnosis. In this perspective, the potential role of soft computing in power plant operation is presented.

1. INTRODUCTION

Parallel to rapid advancements of modern technologies, there emerged a new concept articulated as *complexity*, which is beyond its traditional use. This is partly phenomenological since the concept is generic enough to use in different situations but it is still context dependent and needs to be defined in each case. From the nuclear power plant (NPP) viewpoint the complexity may be understood as multiple interacting processes in a large-scale industrial process environment. In this context, complexity suggests vast amount of data acquisition to be processed during the operation especially referring to three major executions: monitoring, control, diagnostic. Here the problem is the appropriate processing of the data obtained in such a way that the redundancies in processing are avoided and correlations among data are identified to cope with the real-time or other limitations. In this perspective, it is not difficult to realise that the conventional data processing methods may not be efficient enough even though they may be effective enough. This basic conjecture is quite illustrative to indicate why artificial intelligence (AI) technologies should be integrated to NPP environment. Such integration can take various forms like AI-based monitoring, control, diagnostic, maintenance, operator decision support system (ODSS) and so forth.

In the present context, AI is to establish systems that show intelligent behaviour and perform complex data analysis tasks with a level of competence that might even supersede the level of the domain human experts. The characteristic feature of AI is its heuristic nature where the term heuristic refers to knowledge that is used to control the reasoning leading to correct or satisfactory solution.

Two of the major pioneering/preliminary approaches to AI are the *symbol manipulating approach* and *connectionist approach.* Symbol manipulating approach gave birth to expert systems. Connectionist approach is due to neuronal structure in the brain where the complexity is due to the number of the simple operations so that intelligence appears as an illusion as result of cumulating of large numbers of simple connected phenomena. Artificial neural networks (ANN) are the most familiar structure of the connectionist approaches. In the last decade there is a rapid development in the AI technology as well as its utilisation in nuclear industry, in particular power plant monitoring, control and fault diagnosis. The two approaches above for AI have rapidly developed to advanced stages establishing their associated technologies. At the same time they were joined by other AI-based paradigms which have also established their associated technologies before long.

The subject matter of this work is *soft computing* which is processing of uncertain information with the AI methods, that refers to explicitly the methods using ***neural networks, fuzzy logic*** and ***genetic/evolutionary algorithms***. In this respect, soft computing is a new dimension in information processing technology where linguistic information can also be processed in contrast with the classical stochastic and deterministic treatments of data. Referring to this in the context of diagnostic systems in NPPs, the organisation of the paper is as follows. Section two describes the major components of the AI, in perspective. Section three describes an emerging AI technology as a synergistic combination of the existing AI technologies described in the preceding section from the view point of NPP operation. This is followed by the conclusions.

2. PARADIGMS OF ARTIFICIAL INTELLIGENCE AND DIAGNOSTIC SYSTEMS

Artificial intelligence is concerned with the development of systems that emulate the intelligent behaviour of human and further can perform complex tasks. The associated soft computing related paradigms are briefly presented in perspective from the view point of their merits in NPP monitoring and diagnostics.

2.1. Knowledge based expert systems.

Presumably, the first substantial AI attempt was made by means of knowledge-based systems (KBS). KBS provides a convenient way for encoding and storing human knowledge. If this knowledge is from a human expert, then the system is termed as expert system. Such systems supposedly perform on the level of human expert, autonomous reasoning tasks such as diagnosis, decision making. The current status of expert systems is briefly described below.

A first generation expert system is a shallow expert system that consists of knowledge processing unit and a heuristic knowledge base. An expert shell contains no a priory knowledge. It has to be filled with domain knowledge prior to its use. Domain knowledge is captured in production rules. The production rule paradigm is a model for human reasoning. It captures an expert's experience and casual reasoning strategy. It is a representation paradigm where knowledge can be captured in the form of rules. The rules consist of compiled associations of facts and phenomena with solutions and actions. The knowledge base containing these rules is a large set of recompiled chunks of deep knowledge ready to use rather than a collection of shallow knowledge in the form of if-then rules.

In the first-generation expert systems, two fundamental forms of reasoning process is involved. These are forward chaining and backward chaining. Both strategies work on production rules, but complementary. Forward chaining works from antecedent to conclusion, while backward chaining works from conclusion to antecedent. There are several ways for the improvements to increase search speed, performance. However first generation expert systems contain shallow knowledge. Expert systems based on purely shallow knowledge cannot give satisfactory explanations about their behaviour and show abrupt degradation at the edge of their knowledge domain, since no compiled knowledge about cases that never have occurred before is available. Moreover, since knowledge elicitation depends on subjective human experts addressing only a limited number of cases, the expert system's knowledge domain is incomplete and possibly inconsistent of format and meaning. The disadvantages and limitations of first generation expert systems are summarised below [1]:

Incoherent sequences of questions; redundant questions; historical information on a case is not maintained, requiring the user to enter it again for each consultation on that case; inflexible user interface where information is required to be entered in very specific terminology's and formats, otherwise information is ignored; User is nor allowed to revoke an answer or to pursue the effects of an alternative answer; explanations do not cover al the explanation needs of the user; Performance degrades dramatically when dealing with rare case; Inability to recognise that a problem case is at the periphery or outside of its area of expertise; Difficult to modify the system's knowledge. Consistency checks are not facilitated; Inability of the system to evolve on the basis of its experiences in problem solving.

The causes of disadvantages and limitations above are explained as follows:
Shortcomings of reasoning knowledge that it is not complete; the generic tasks and strategies are implicit; shortcomings of domain-factual knowledge due to its structure which is not compatible to the way human experts model their knowledge.

The causes all originate from the differences and incompatibilities between human and expert systems knowledge representation and processing. Referring to the shortcomings of the first generation expert systems, the second-generation solutions are briefly as follows. In second generation expert systems, knowledge is derived from the first principles introducing generality. However this does not imply that the resulting model precisely describe the physical model because the first principles are not detailed enough for the complexity of the real world.

Designing a second-generation expert system with the objective to overcome a specific first generation limitation without solving this limitation in the context of others is prone generating local, non-robust solutions. For sound improvements in second generation expert systems, the limitations in the first generation counterpart must be well understood. Hence, the architecture should then be designed from the perspective of the root causes and not of their effects. Then, the architecture will provide a global and thus effective solution. Integrating first and second generation expert systems should make it possible to use heuristic knowledge to decide when to carry reasoning back and forth from heuristics to first principles. This is important when experience fails or is lacking or when the domain model is incomplete. Efficiency and the ability to reason progressively ensure that model-based reasoning is performed in time. This is very important for critical situations where response time should be small to avoid imminent accidents. A progressive reasoning mechanism generates a preliminary answer using only a very small knowledge base. While time is available, gradually larger knowledge bases are accessed to refine this answer step by step. After some time, the current inference takes the precedence.

In spite of inherent limitations, expert systems can be quite effective and efficient diagnostic tool in plant diagnostic applications. However in their safety related applications care should be exercised. Some guidelines for such cases are summarised below [2].

- The expert system should be based on the best possible risk analysis;
- The quality of the risk analysis should be checked, especially for completeness;
- Advice rules should be expressed in terms of possibility rather than probability;
- The system should be robust, so that in cases of doubt safe advice is given;
- For each advice rule, the range of possible contexts in which the rule may be applied should be evaluated;
- The system should be designed to provide support to the operator, rather than safety actions, so that the need for safety actions can be avoided.

2.2. Neural Networks

Neural network is a data processing system consisting of a number of simple, highly interconnected processing elements in an input/output architecture. A neural network is a distributed information processor where structural information can be stored and can be made available for use in later reference. It resembles the brain functions because the network through a learning process acquires knowledge and the information/knowledge stored is distributed in the form of connection weights of the network structure. A feed-forward neural network is generally structured with a set of a prescribed number of elementary processing units arranged in several layers. The very first layer that is, input layer, external information is coupled to the network. Each subsequent layer receives the information provided by the immediate lower level and sends the processed information directly to the upper layer. The output layer delivers the final processed information for use in the intended application. There are many variants of feed-forward structure, as well as many other variants of the neural network structures.

Neural networks found rapid and vast interest in plant operation especially in monitoring, diagnostic and control due to their potential for fault detection and non-linear characteristics. For monitoring and diagnostics, perhaps the most important generic structures are first self organising networks due to their classification ability used for large data classification and reduction before processing [2-4] and second feed-forward structure in auto-associative form [5-10] due to its special features. The architecture of autoassociative network is shown in Fig.1. The measurements from the plant sensors are applied to the input of the network. The input measurement vector is non-linear mapped to bottleneck layer. Subsequently, the mapped information is non-linear de-mapped to the output layer of the network. The bottleneck layer (hidden layer) plays important role in the effectiveness of the network. It has a dimension, i.e., number of nodes smaller than that at the input or output. It prevents a simple one-to-one mapping as result of training and the least-square training criterion assures that the internal representation developed by the network contains the maximum information it can accumulate with the existing structure.

The non-linear mapping and de-mapping provides that, in such multivariate plant monitoring, the network can be much more sensitive to process changes, and may help to highlight incipient problems (early fault detection) before they become obvious yielding serious problems.

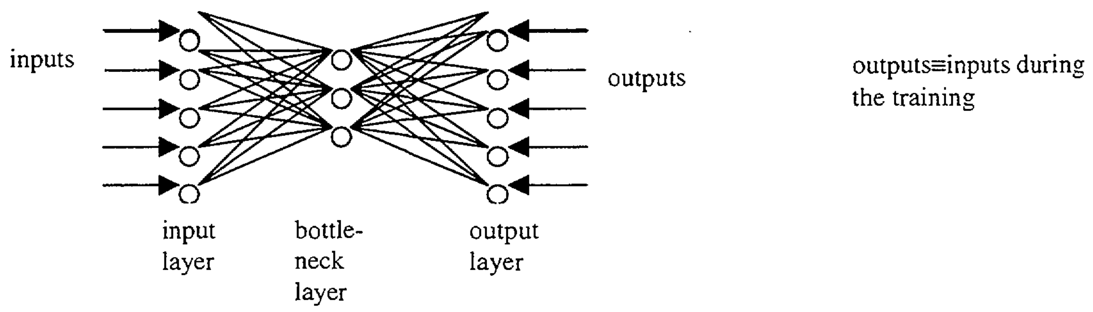

Figure 1 . Architecture of the auto-associative network

One more important feature of autoassociative network is that it plays the role of noise filtering. This can be seen as follows. Presently, we assume inputs to the network are plant measurement vectors. The training set is formed by the collection of these vectors, each of which belong to different times and plant conditions in the operation. The variations within the set of measurement vectors consist of operational changes, process disturbances and the associated control system responses together with process and measurement noises. Since as the result of training the correlation between the process signals (measurement vector components) are established, the uncorrelated variations are excluded, i.e. filtered out. The process noise is correlated since the measurements are coming from the same process. However, measurement noises are uncorrelated and their effects are eliminated that it results in improved training yielding improved estimation of the measurement vector at the output. The positive effect of the noise filtering can be observed also by introducing additive white noise on the process signals in the measurement vector before training. Enhanced training performance due to noise filtering phenomenon of auto-associative network with plant signals is reported in the literature [11] and it is termed as *robust training* [10].

Due to their non-linear characteristics, neural networks are also used for preliminarily non-linear control of diverse applications as a part of neural network research. Today, firm foundations of system identification and control of dynamical systems using neural networks is established [12,13]. For power plants, improved safety demands require new control laws to perform novel control functions with novel supervision and plant control concepts [14]. In general, when the uncertainties in a process environment are 'large', the common feedback controllers may not be satisfactory enough. Adaptive controllers may be the solution by adapting the system dynamics parameters in the model. However, in a plant environment there are cases where one need to significantly increase the operating range. This requires dealing effectively with significant uncertainties of the complex dynamic system in addition to increasing the validity range of the control methods. Alternatively, this requires coping with significant unmodeled and unanticipated changes in the plant, in the environment and in the control objectives. This is the issue of non-linear and intelligent control where neural networks play important role.

2.3. Fuzzy Logic

Fuzzy logic conventionally is a generic name including the fuzzy set theory, fuzzy logic itself and the associated technology. Fuzzy set theory was introduced through Zadeh [15]. With fuzzy sets, a numerical value is classified into one or more linguistic labels. These labels may be discrete as well as continuous and they are coined as membership functions that represent the numerical strength of linguistic labels for the domain of classification. Since the membership functions can overlap, this results in multi-value representation of the knowledge. An input value intersects with one or more membership functions of the input classification and therefore it is attached to several linguistic labels.

A fuzzy set **A** on the universe X is a set defined by a membership function μ_A representing a mapping

$\mu_A : X \rightarrow \{0,1\}$

where the value $\mu_A(x)$ for the fuzzy set **A** is called the membership value of $x \in X$. The membership value can be interpreted as the degree of x belonging to the fuzzy set **A**. A typical membership function might be as shown in Fig.2.

Before entering a fuzzy system, the information at hand is fuzzified. This is done by an input classification, matching the input value against a chosen set of linguistic labels. These labels partly overlap as shown in Fig.1, so that a numerical value can be classified into more than one label, each with an associated member value. Inference is carried out with evaluating fuzzy production rules where the propagation of the fuzziness is linear with respect to arithmetic operations. Logical combinations are performed in a systematic way with certain rules known as norms. The extension of the intersection and union of two classical sets to the intersection and union of two fuzzy sets is not uniquely defined. However, intersection and union operations for fuzzy sets should have the counterpart intersection and union of classical sets.

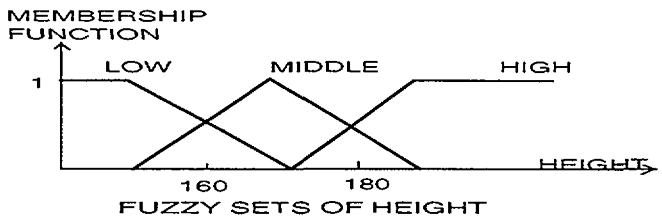

Figure 2: Representation of fuzzy sets of heights

Zadeh · proposed to use the following definitions

$$\mu_{A \cup B} = \min(\mu_A(x), \mu_B(x))$$
$$\mu_{A \cap B} = \max(\mu_A(x), \mu_B(x))$$

If we restrict $\mu_A(x)$ and $\mu_B(x)$ to values $\{0,1\}$, then these operators reduce to the intersection and union as defined for classical sets. Since one linguistic value can be attached to several numerical values in the context it is considered, more than one rule might be triggered producing several answers. This multiple answer can be combined to reach an optimal decision or a decision region. This is illustrated in Fig.3.

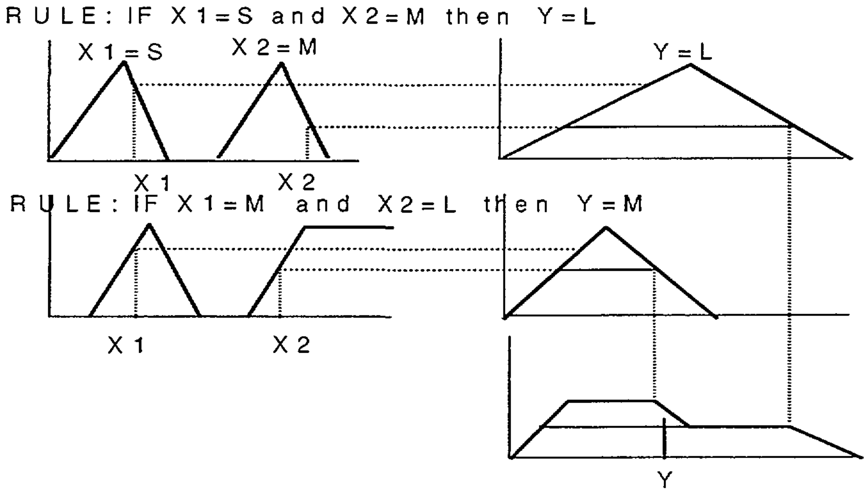

Figure 3: Fuzzy inference

Among the industrial applications fuzzy logic control become very popular in the last decade. However, referring to conventional fixed feedback and/or adaptive control in a power plant environment for fault diagnosis and safety, such exercises is not to conceive. In this respect the followings are useful to remember [16]:

Fuzzy controller should not be used when

- conventional control theory yields a satisfactory result;
- an easily solvable and adequate mathematical model already exists;
- the control problem is not solvable/system is not controllable.

However, in complex, dynamical systems to meet the demand of intelligent decision-makings for various purposes fuzzy logic may play important role. Among such decision-making needs, fault diagnosis and intelligent/autonomous control takes important place where intelligent decision making is required to generate appropriate control actions. Fuzzy logic functionality is enhanced by fuzzy neural systems and they are subject matter of soft computing.

2.4. Genetic/Evolutionary Algorithms

Genetic algorithms (GA) [17] are stochastic search techniques having inspiration from the natural selection and genetics. They can be used in different ways and can play the key role in intelligent systems, as they can easily be corporate in such systems. Presumably, they are mostly articulated as powerful optimisation algorithms the criterion of which is termed as *fitness/evaluation function*. The linguistic quantities can also be integrated into the optimisation scheme, as is the case in fuzzy logic. GA type optimisation algorithm is conceptually flexible so that it is also used in applications where the conventional optimisation algorithms may be prevalent such as neural network training problems. In this particular example the motivation may be to avoid the risk of hanging on the local minima during the training. Another significant application example might be the optimal membership function determination or fuzzy IF-THEN rules identification in fuzzy-logic-based intelligent systems.

3. SOFT COMPUTING

Soft computing (SC) deals with the processing of uncertain information with AI methods. As the concept of uncertainty is different than the classical analytical paradigm, the treatment of the uncertainty itself is subject to uncertainties, such as membership function determination, for instance. Even this simple example indicates that the soft computing as an innovative approach to constructing computationally intelligent systems, is not an easy task. It is an emerging approach to computing having the reasoning of human as a counterpart in decision-makings.

In the preceding section the tools of SC are presented. From the industrial application point of view, neural network technology and fuzzy logic technology and other AI technologies are in the course of fusion forming a counterpart technology known as SC technology. From the nuclear industry viewpoint, SC technology is quite appealing due to following reasons:

- Handling of the non-linearity and approximate dynamic system model provisions and other provisions of a large scale system is relatively easy;
- Intelligent decision makings are produced where due to the complexity of the power plant the necessity of such decisions inevitably exist;
- Expert knowledge base systems can be formed and they may be effective in plant's diagnostic use over the first and second generation expert systems;
- Relatively easy to device as goal-oriented dedicated systems;
- Provide new methods, methodologies and the associated paradigms which are essential for cross validations;
- Individual deficiencies of AI tools are eliminated by joint involvement in the application.

The power of soft computing can be attributed to the following features:

- SC is a sub-domain of a well-established area in Electrical Engineering known as **Non-linear System Identification**
- Neural and fuzzy systems have ample common working area where both methods can individually be applied with the associated trade-offs;
- The tools of SC are closely related and co-operative though, seemingly this co-operative feature is not apparent;
- SC technology is already established. Powerful commercial software and hardware is available.

Referring to the first item above, the system identification and soft computing methods with their relevance are shown together in Fig.4.

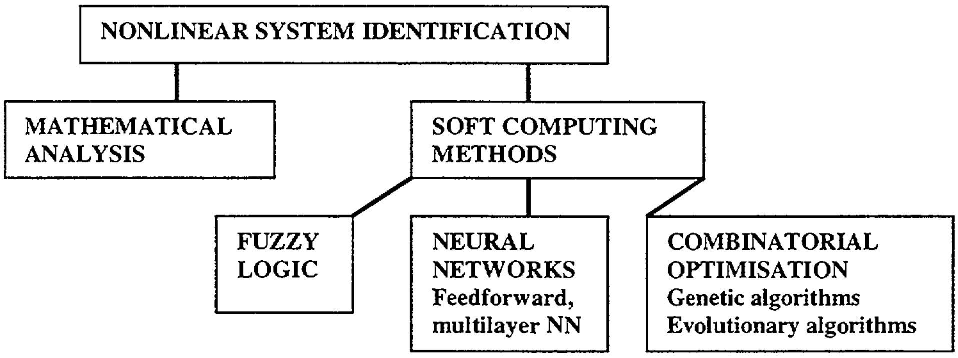

Figure 4. Nonlinear system identification methods and some associated paradigms

It is possible to consider the non-linear system identification in a unified form so that mathematical analysis methods and the soft computing methods can be investigated in a single framework [18]. In this case the problem becomes a multivariate function approximation of the form

$$f(x)= \sum_{i=1}^{k} w_i \, \Phi_i \,(x) \tag{1}$$

i.e., weighted sum of basis function, where $\Phi_i(x)$ is the base function; w_i is the weight factor. The base functions can be selected as the soft computing application requires. In case base functions are selected to be Gaussian functions, the neural network counterpart of the equation becomes radial basis function (RBF) networks. The NN topology of the RBF network is shown in Fig.5.

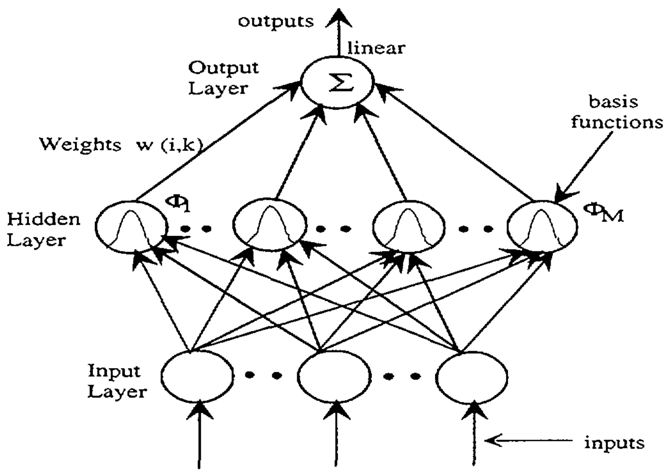

Figure 5. Radial-basis function network topology

It is interesting to note that, the RBF structure in Fig.5, is the same structure of a fuzzy logic where Gaussian functions play the role of Gaussian membership functions [19]. Such a counterpart network representation of fuzzy logic is termed as fuzzy logic network. Inputs and outputs of the network correspond to appropriately determined input and output fuzzy vectors respectively. In such a scheme, the training of the NN would result in the accurate assessment of the fuzzy membership functions in fuzzy logic.

Further different selection of the base functions in Eq.1, gives further different associated interpretations to the equation. In the context of SC, following interpretations are far reaching:

- The base functions are sigmoids. Then the corresponding NN structure becomes feedforward multi-layer perceptron (MLP) network;
- The base functions are wavelet functions. Then function approximation becomes multiresolution wavelet decomposition of the function which exibits a number of interesting properties [20] and they find powerful applications in plant operation and monitoring [21-22];
- The base functions are wavelet functions. Then the corresponding NN structure becomes wavenet networks (WN) [23]. Since wavelet functions exibit special properties, the network also possesses special features in SC. One interesting property can be exercised by means of orthogonal wavelets so that orthogonal membership functions in fuzzy logic are obtained for special SC applications.

The unification of SC methods through Eq.1 is schematically shown in Fig.6.

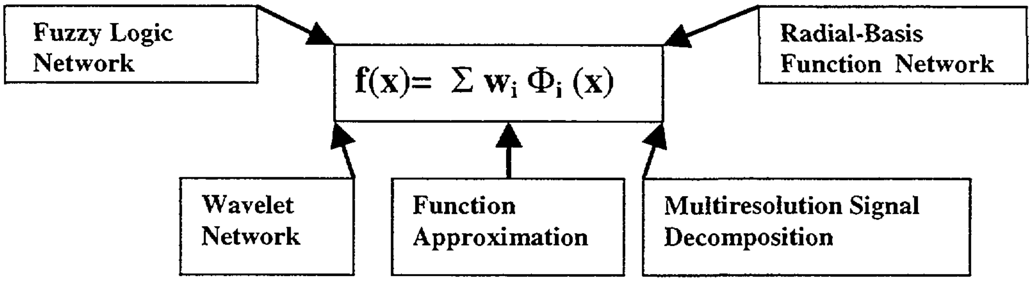

Figure 6. Unification of soft computing methods

From the power plant operation viewpoint, most soft computing implementations can be viewed as intelligent applications using a knowledge base, as they supposedly possess domain expert knowledge. In the network representation of fuzzy logic as counterpart of RBF networks, each node at the hidden layer (Fig.5) corresponds associated fuzzy IF-THEN rule.

Soft computing technology play important role in nuclear power plant operation [24- 29].

As an alternative to the network representation of fuzzy logic as knowledge base, another fuzzy logic approach is fuzzy associative memory (FAM) [30] which has the interpretation as fuzzy computation with matrices that they are referred to as FAM matrices. The fuzzy input vector in fuzzy logic network above, is used to form a product with associated FAM matrix so that the output is a fuzzy vector of a multivalued logic. Here, each FAM matrix corresponds to a fuzzy IF-THEN rule, as before.

4. CONCLUSIONS

Neural, fuzzy and other intelligent technologies are joining on a common place known as soft computing. Soft computing technology has important applications in power plants since the support of intelligent technologies in man-machine interfaced complex integrated systems is desirable to meet the general demand of high information processing capacity, required in such systems. This is basically due to the complexity where many interactions within the system take place so that conventional decision-making procedures or plant control schemes need to be supported by intelligent means. Soft computing is an emerging intelligent approach with the associated technology especially addressed for industrial applications. The theoretical foundations of the approach is rather sound. Presently, it is plausible to talk about grey rather than black box, due to the recent advancements in the NN research. The unified representation of soft computing is a milestone as this representation clearly points out the mathematical foundations of soft computing and its relevance to other mathematical methods and the associated disciplines. In this respect, SC will continue to benefit substantially from other disciplines and apparently the progress on soft computing will keep on its rapid pace.

From the diagnostic systems viewpoint in power plants, as an alternative, soft computing is a new approach for the followings tasks:

- Intelligent monitoring;
- Intelligent control;

- Expert system control;
- Intelligent decision support.

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