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The Application of Neurofuzzy Systems in Intelligent Fault Diagnosis

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Abstract

Fault diagnosis is a crucial step in all industries to ensure high quality, cost efficiency, reliability as well as safety. As the complexity of the current machinery system is increasing, fault tolerance become more and more crucial. The conventional signal-based techniques can no longer detect fault occurrences effectively. A more analytical or knowledge-based approach is required in this case. The development of neurofuzzy system, a hybrid technology of fuzzy logic and artificial neural network, has made it to be suitable in intelligent fault diagnosis due to its high learning and adaptive capability. In this paper, the algorithm and architecture of fuzzy model, neural network and the neurofuzzy system are discussed. Its applications in machinery fault diagnosis are also addressed.

Keywords: Neurofuzzy, machinery fault diagnosis, neural network, fuzzy logic.

Introduction

Fault is an inevitable issue for machineries. All machines are subjected to fatigue, deformation and wear after going through a long operating time. Some of the common types of machinery fault include misalignment, unbalance, and bearing fault[1]. These faults, if left untreated, in turn will increase the vibration level, eventually causing machinery breakdown. Therefore, it is crucial to establish a suitable machinery fault diagnostic system to constantly monitor the operating conditions of plants and machineries in order to detect any abnormal symptoms of breakdown. However, machinery fault detection can be difficult for systems with high complexity level, introducing more uncertainties into the diagnosis process.

Neurofuzzy system or fuzzy neural network is a well-developed solution to overcome the weaknesses of other methods[2]. Fuzzy logic utilizes fuzzy sets and a linguistic model consisting of a set of IF-THEN fuzzy rules to mimic human reasoning style in the diagnosis[3]. Neurofuzzy computing aided machine fault diagnosis involves artificial intelligence (AI), thus providing an effective and yet appealing problem solving network. The methodology of neurofuzzy system is well-suited in tackling faulty parts in machineries and plants due to its ability in dealing with both linguistic and quantitative data.

In 1994, J. Zhang *et al.* presented a newly developed method for on-line process fault diagnosis through the use of fuzzy neural networks[4]. In 2008, a fault diagnosis technique based on multi-sensor information was introduced by Yang *et al.* to overcome the limitation of the current fault diagnosis methods in hydraulic systems[5]. In the same year, Ma *et al.* proposed a fuzzy neural network method used in thermal system fault diagnosis under different operating points[6]. These studies have facilitated the further understanding of the interactions between fault diagnosis and neurofuzzy system.

Related works

Different types of machinery fault diagnosis were introduced besides neurofuzzy system, each with their own strengths and weaknesses. Some of these well-developed diagnostic methods include vibration analysis, tribology as well as infrared thermography analysis.

Vibration analysis: Vibration analysis is a commonly used condition monitoring method in the industry. A change in the vibration signature in machinery can be used to extract different information about its internal structural defects before they become critical[7]. The fault type involved can be determined through analyzing the time and frequency spectrums with the use of suitable signal processing techniques.

Vibration analysis has been introduced in early 60's due to development of Fast Fourier Transform (FFT) mathematical method in 1964 and portable spectrum analysis equipment. The use of vibration diagnosis in machinery faults experienced further growth after the invention of portable FFT-based data collectors in the 80's. Nowadays, on-line dynamic vibration monitoring system is widely applied for monitoring mechanical vibration in plants and machineries. Piezoelectric accelerometers are used for this purpose while vibration probes and computer-based data acquisition systems are used in acquiring and storing FFT data. These data will be interpreted and analyzed by vibration analysts. Moreover, recent researches discovered that the combination of vibration analysis and wear debris analysis offers more reliable and accurate information, which in turn improving the effectiveness of the condition monitoring system in general[8].

Tribology: Tribology is the study of friction, wear, lubrication and contact mechanics, particularly in the mechanical engineering context. This analysis is effective in predicting the onset of damage in machineries and plants. Sometimes, the practical application of tribology within maintenance field is referred to as Industrial Oil Analysis.

In a tribological oil analysis, the wear process is monitored where this information remains linear at steady state but close to exponential at catastrophic wear. The VTT Diagnostic Circle is used in this method to investigate the process of on-going processes in diagnosis from contact mode analysis, signal analysis up to prognostics and maintenance decisions [9]. Some of the common instruments used in this diagnosis include particle analyzer, electron probe micro-analyzer (EPMA) and confocal laser scanning microscope (CLSM).

Infrared thermography analysis: Infrared scan is another popular machinery fault diagnosis that determines the significance of hot spots and abnormal heating patterns found in equipment[10]. This enables analysts and operators to locate and repair the machinery fault before they turn out into catastrophic failure. The analysts, or more specifically thermographers, are trained to locate a potential issue by detecting the relative heat differential in machinery equipment and make a judgment as to what that data indicates. Generally, the presence of heat indicates resistance, which is most often related to failing parts, loose connections, corrosion or load imbalance, causing vibration and friction.

Principles of neurofuzzy logics

Fuzzy inference can be summarized as a method that interprets the values in the input vector and, based on some set of rules, assigns values to the output vector. It has the ability to process and analyze data in both numerical and linguistic form. Neural network was developed as an attempt to realize simplified mathematical model of brain-like system. Its main strength is the ability to learn while being in used. By merging both fuzzy logic and neural network to form neurofuzzy system, the merits from both systems can be combined together to form a more powerful tool to be applied in machinery fault diagnosis. 'Neurofuzzy' is defined as the combination of techniques from both fuzzy logics and neural networks[11]. This combination can be explained as a fuzzy system developed through the use of heuristic neural-network-based learning methods.

Fuzzy logics: The theory of fuzzy set has been first proposed by Prof. Zadeh from three decades ago[12]. In this paper, fuzzy set is defined as a class of objects with no sharp boundaries. In a fuzzy set A of a universe of discourse X, every element in X is assigned a value ranging from 0 to 1 by a membership function $\mu_A(x)$, where this value signifies the membership level[13] of x. The fuzzy set A in X can be generalized as:

$$A = \{(x, \mu_A(x)) \mid x \in X\} \qquad (1)$$

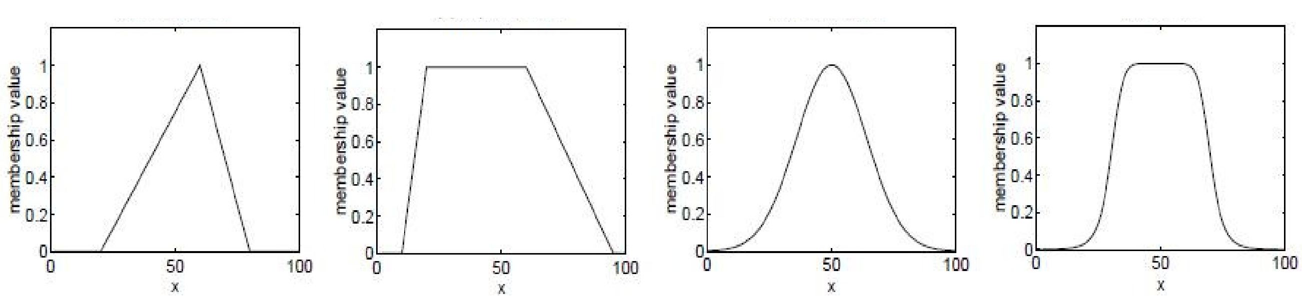
Different types of membership function are available in fuzzy set[14]. Some examples include Triangular, Trapezoidal, Gaussian, Generalized Bell, and the Sigmoidal functions[15-16]. The graphs of these membership functions are shown in figure-1.

Fuzzy logic systems is a non-linear mapping of a vector input to a scalar output through applying a set of IF-THEN rules defined by researchers[17]. A fuzzy If-Then rule can be generalized as generalized as:

If x is A Then y is B (2)

Where 'x is A' acts as the antecedent or premise while 'y is B' is the consequence or conclusion. Upon these If-Then rules, fuzzy reasoning is performed.

Figure-2 shows the block diagram of a fuzzy inference system[16]. The first step in the fuzzy reasoning is to convert the input, either crisp or fuzzy, to a linguistic variable using the membership functions stored in the fuzzy knowledge base. The set of If-Then fuzzy rules is then used to map the fuzzy input to fuzzy output. Lastly, a defuzzifier converts the fuzzy output of the inference engine to crisp output through the use membership functions which are analogous to that used by the fuzzifier. Fuzzy reasoning can be categorized into two main types, which are Mamdani and Sugeno models.



(a) Triangular MF (b) Trapezoidal MF (c) Gaussian MF (d) Bell MF

Figure-1
Different graph types of Membership functions[15-16]

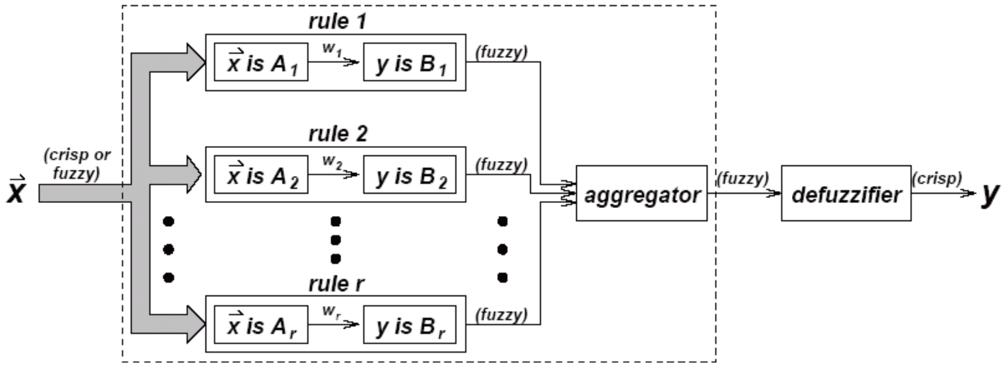


Figure-2
Block diagram of a fuzzy inference system[16]

Mamdani's model: The first type of fuzzy inference systems is the Mamdani's model[18]. The original goal of this model is to control a steam engine and boiler combination through the use of a set of linguistic control rules obtained from human operators. This model has the following form for a Two-Input-Single-Output (TISO) system. The model has the form:

If x is A and y is B Then z is C (3)

Where A and B are fuzzy sets of the universes of discourse X and Y. Figure 3 shows the Mamdani's fuzzy reasoning scheme for multiple rules and antecedents using max-min composition.

Sugeno's model: Another fuzzy reasoning system is the Sugeno's model[19]. Its primary goal is to generalize fuzzy rules from a given input-output data set. The generalized form of Sugeno's model for a TIS0 system is: as:

If x is A and y is B Then z = f(x, y) (4)

Where A and B are fuzzy sets of the universes of discourse X and Y while z = f(x, y) is the crisp function, very often a polynomial function with respect to x and y. Figure-4 shows the first order Sugeno's fuzzy reasoning scheme, where the weighted average shown is effective is avoiding time-consuming defuzzification process.

Neural network: An artificial neural network (ANN) is an information processing system that acts as the simplified model of brain to transform inputs to outputs to the best of its ability. It has been applied successfully in many applications such as pattern recognition[20], robot navigation[21], optimization of water treatment process[22], estimation of global solar radiation[23] and etc. More formally, Herve Abdi has defined neural networks as adaptive statistical models based on the brain structure analogy where 'adaptive' in the definition means that the network is capable of learning how to estimate the parameter though the use of some exemplars[24].

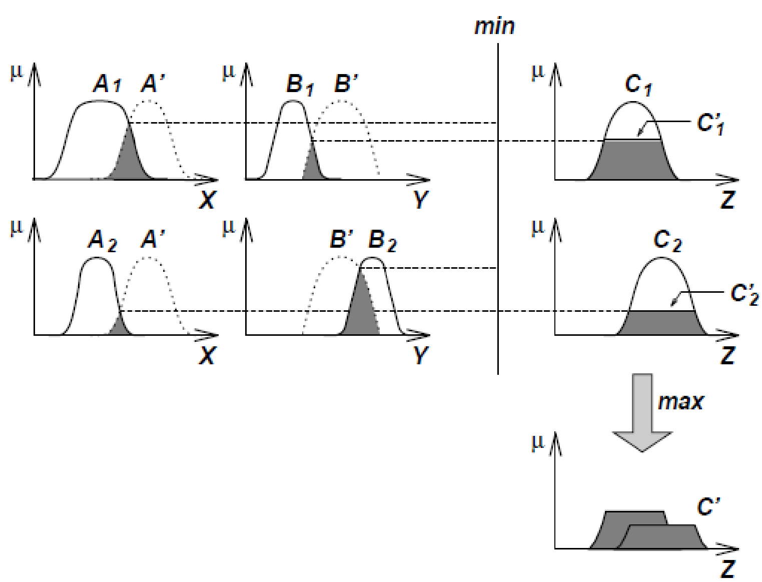


Figure-3
Mamdani's fuzzy reasoning with Max-Min composition[18]

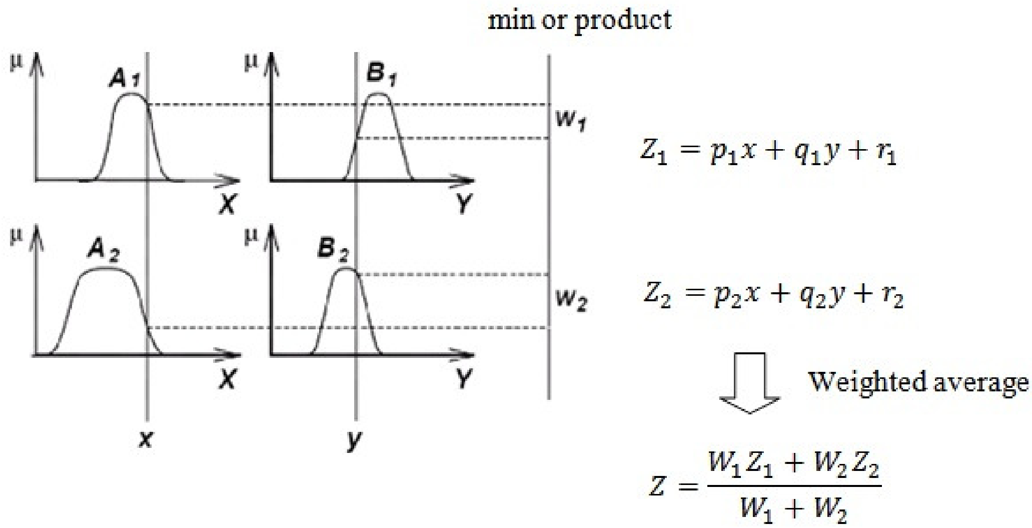


Figure-4
Sugeno's first order fuzzy reasoning scheme[19]

An ANN is composed of a large number of artificial neurons that cooperate to perform the desired function. The connections artificial neurons mimic the synaptic connection characteristics of the biological neurons. Every artificial neuron has a set of inputs x_i, where each of these inputs signifies the output of another connected neuron. Each input is assigned with a weight, analogous to the synaptic strength, before sending to the main body of the processing element. The initial weights of an ANN are crucial in determining the convergence speed of the training algorithm. These weights will be adjusted through a learning procedure in the ANN called learning rules where the value of the weights are renormalized at every training epoch[25-26].

Basic building blocks: An ANN consists of a large number of basic units or artificial neurons arranged in layers as shown in figure-5. They are connected together with a synaptic weight which will be multiplied together with the input data for amplification of attenuation purposes.

The weighted sum of the inputs is computed as:

$$a = \Sigma x_i w_i \quad (5)$$

This output a is further transformed into the output data O through a transfer function f(a):

$$O = f(a) \quad (6)$$

The most common transfer function used is the logistic function:

$$f(x) = 1/(1 + e^{-x}) \quad (7)$$

The behavior of the ANN is determined by the transfer functions used by the neurons and the synaptic weights set here[24,27-28].

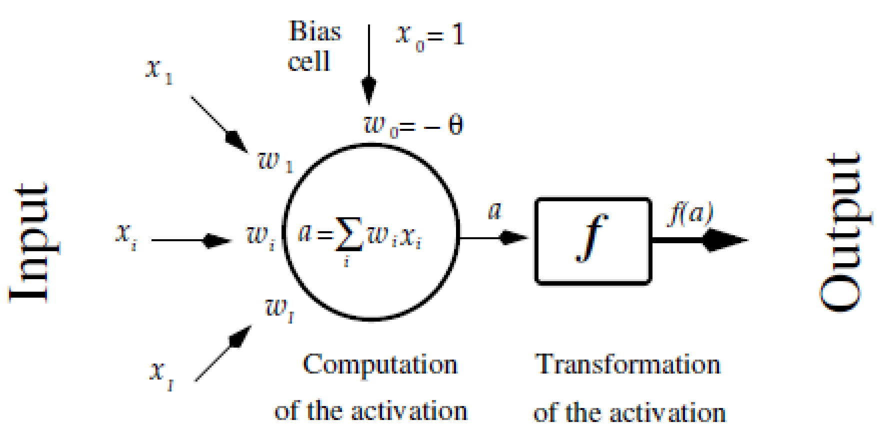


Figure-5
Basic building block of ANN[25-26]

General architecture: The arrangement of artificial neurons into layers and the connection pattern within and between the layers forms the ANN architecture. The most common architecture for ANN is the multilayered perceptron as in figure-6.

The architecture type used for a specific application should be chosen based on a few issues including the topology of the network (multilayered, single-layered, or recurrent), data flow (recurrent or non-recurrent), types of input values (binary, bipolar or continuous) and the forms of activation (linear, step, or sigmoid). Some of the common ANN architectures used in industrial applications are Kohonen Networks, Adaptive Resonance Theory (ART), Polynomial Networks, Probabilistic NNs (PNNs), and Cellular NNs (CNNs) [26].

Neurofuzzy system: Neurofuzzy system combines the techniques from both fuzzy logics and neural networks by applying the learning algorithm of ANN in parameter identification of fuzzy models[11, 29]. The evolution of neurofuzzy system started in the early 1990s with NN oriented architectures like ARIC which is later developed into fuzzy network architectures such ANFIS and NEFCON [30].

ARIC: In 1991, Berenji introduced one of the pioneer neurofuzzy systems called the ARIC model (Approximate Reasoning-based Intelligent Control) [30-31]. Figure-7 shows the architecture of ARIC. The main elements in this architecture include the action evaluation network (AEN-offers advice to the main controller), the action selection network (ASN-has a fuzzy controller) and the stochastic action modifier (SAM-modifies the action based on ASN and internal reinforcements obtained from AEN).

The ARIC architecture resembles human learning skills by having an embedded fuzzy controller and applying multi-layered NN in ASN. This allows the system to be able to learn, through a certain number of trials, search heuristics as a probabilistic mapping from input to output followed by a stochastic modification of action based on the fuzzy controller.

The ARIC algorithm starts with the state evaluation of the system by AEN to find out the occurrence of failure in an input. An internal reinforcement is generated by AEN based on this evaluation. Action is decided by ASN through fuzzy rules of the system. The output is then used by SAM to generate its respective action to be transmitted to the dynamic system to transform it into a new state. Evaluation is done by AEN to compare the new and old states. The new internal reinforcement will determine the weight adjustment as the learning process. With sufficient learning repetitions, the whole system is improved to be more reliable.

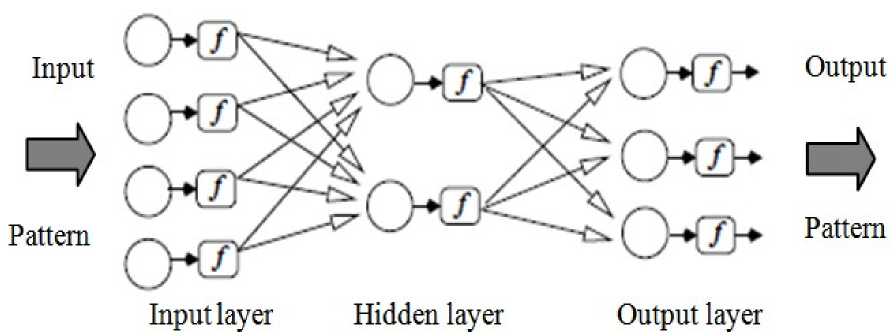


Figure-6
A multilayered perceptron

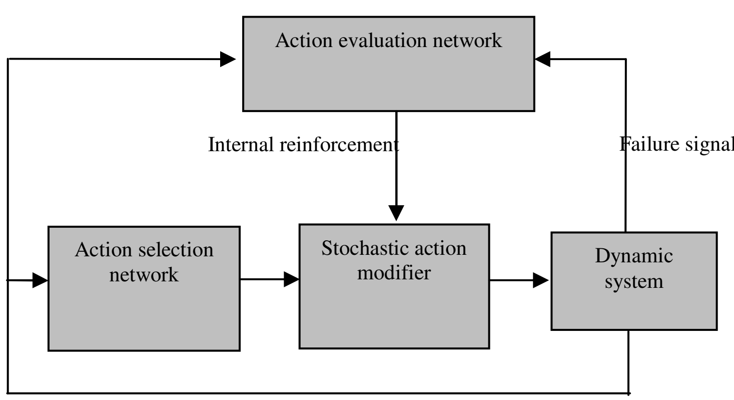


Figure-7
Architecture of ARIC[30-31]

Nefcon: In 1994, Nauck introduced a new model of neurofuzzy systems called the NEFCON (Neuro Fuzzy Control) which works on the basis of the architecture of a fuzzy perceptron[30, 32]. It offers a learning algorithm which is capable of learning the fuzzy sets and fuzzy rules of a fuzzy controller through the back-propagation of fuzzy error measure. Its specialty is that it avoids the same linguistic terms from being defined by more than one membership functions. Figure-8 shows a NEFCON system with two input variables and five fuzzy rules which eventually results in the single output. The nodes at the input layer, $\xi_{,1}$ and ξ_2 represent the input values while η is the output value. The middle nodes R_1, R_2, R_3, R_4 and R_5 are the five fuzzy rules involved which μ_r and V_r are the antecedents and consequents of the fuzzy set respectively.

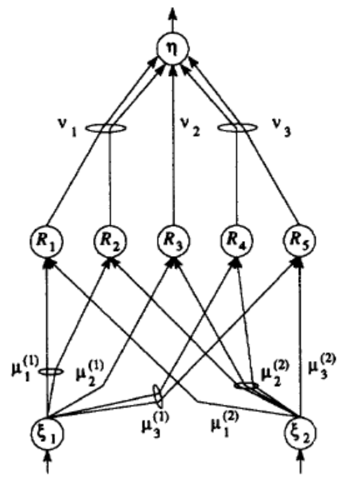


Figure-8
NEFCON architecture with 2 Input variables, 5 fuzzy rules and 1 output[30,32]

In contrary to NN, NEFCON connections between layers are assigned its weight in terms of fuzzy set instead of a real number. Ellipses drawn at the connection lines represent the shared weight or the rules using similar antecedent. The input unit signifies the fuzzification phase, followed by the inference logic as the propagation function and lastly the output unit as defuzzification.

There are two main phases in NEFCON learning algorithm. The first phase is to learn the specified rule set while the second phase is to modify the rules fuzzy set for optimization purpose. The similarity of both phases is that they involve the measure of fuzzy error to determine the optimized state of the system rule base. To adjust the membership functions of these rules fuzzy set, Fuzzy Error Back-propagation (FEBP) algorithm. The principle of this algorithm works based on the output result where the weight of the rule will be increased if the output is rewarding or decreased if the output is punishing. The condition for this algorithm to function is that the prior knowledge of the system or the rule base of fuzzy rules must be available.

ANFIS: In 1993, Jyh-Shing *et al.* presented ANFIS (adaptive neuro fuzzy inference system) which is a pioneer fuzzy-neoro model[30,33]. With this hybrid learning algorithm, the human-predefined fuzzy rules can be optimized to better explain the relationship of the input and output data. if no prior knowledge on the system is present, an intuitive membership function can be defined to initiate the learning algorithm and develop its own fuzzy rule base. Figure-9 shows the ANFIS using Sugeno model with two inputs x and y and a single output z. For the first order of this model, the two fuzzy rules implemented are:

Rule 1: If x is A_1 and y is B_1, then $f_1=p_1x+q_1y+r_1$ (8)
Rule 2: If x is A_2 and y is B_2, then $f_2=p_2x+q_2y+r_2$; (9)

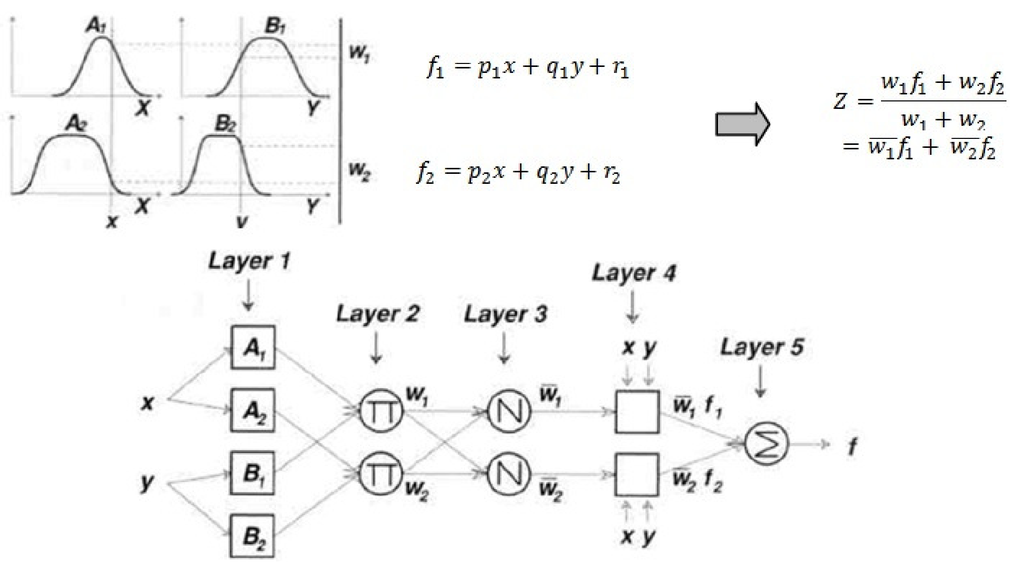


Figure-9
First order Sugeno modeled ANFIS and its architecture

There are four hidden layers in this architecture. The first layer is the fuzzification phase of input data while the second layer uses T-norm operators to process the antecedent of the rules. The third layer is the rule strength normalization phase while the fourth layer determines the parameters of the rule consequents. Lastly the output layer produces the output by summing up all incoming data.

One of the issues to be concerning while training ANFIS, as mentioned by Jang, is to retain the human plausible characteristics of the systems including the bell-shaped membership functions and minimal uncertainty. Minimum uncertainty brings the meaning that the final output should be determined by the major fuzzy rule instead of several fuzzy rules with the same firing strengths. To keep the uncertainty to its minimum, a modified error measure can be used.

$$E' = E + \beta \sum_{i=1}^{P} (-\overline{W_i} \times in\overline{W_i}) \quad (10)$$

Where E is the old squared error, β is the weight constant, P is the training set size and $\overline{W_i}$ the normalized firing angle at *i*th rule.

Intelligent fault diagnosis: Fault diagnosis is generally working on the principle of the generation of signals called residual which reflect operating inconsistencies between the normal and faulty system[34]. Faults that appear in machinery systems can be groups into three general categories[31], namely actuator faults, component faults and sensor faults as shown in figure-10.

To prevent these faults from being left undiscovered and eventually leading to breakdown, three subtasks in machinery fault diagnosis: fault detection, isolation and analysis, have to be performed. For the subtasks to work effectively, concepts on residual generation evaluation is crucial to be incorporated into the machinery system[35] as shown in figure-11.

With the increasing complexity of the current machinery system, the occurrence of fault has become harder to be detected as it tends to concern more on multiple simultaneous faults. To solve this issue, neurofuzzy network has proposed to be used and growing more popular among researchers. The use of fuzzy logic enables the system characteristics to be determined in terms of simple IF-THEN rules for easier understanding of the factors of fault occurrence[17]. Meanwhile, ANN has the capability of learning and modeling non-linear functions which usually appear in industrial applications[24]. The hybrid neurofuzzy technology is therefore combining the merits from both method to develop a fault diagnosis technique which mimics human analyzing and reasoning skills.

The fault diagnosis based on neurofuzzy system has the function of collecting various residual signals, comparing and analyzing the signal amplitude with the predefined thresholds, and lastly determine the fault type and tits respectively level of severity. In general, fault diagnosis with neurofuzzy system[36] can be divided into five main phase shown in figure-12. Diagnosis target and signal acquisition phases collect the real-time residual signals from the target system to reflect its latest condition. Fuzzy pre-treatment, neural network and diagnostic analysis will form the decision making module in the system to determine the fault occurrence, fault type and its severity level.

A recent study of the neurofuzzy based fault diagnosis is the fusion fault diagnosis technology proposed by Na Deng *et al.*[37] in 2012. In this paper, BP neural network is used to meet the main concern of this model credibility. Diagnostic result is obtained after the fusion of evidence theory deduced from predictions of several sources. This has improved the overall reliability of the system and output as the evidence theory is not solely depending on the experts' knowledge, experience but also take into account the repeated faults and diagnosis results. Therefore, the accuracy of fault identification can be improved by avoiding a single signal source which might be incomplete or fuzzy.

Figure-13 shows the flowchart of the system troubleshooting procedures of the diagnostic process. From the flowchart, it can be deduced that the algorithm works mainly based on forward reasoning.

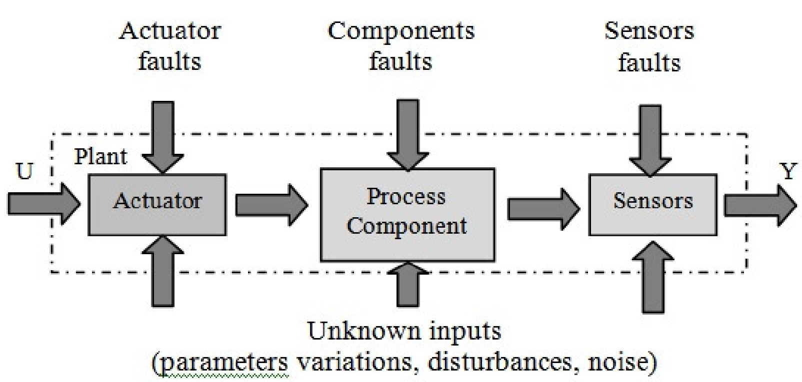


Figure-10
Categories of faults in machinery systems[35]

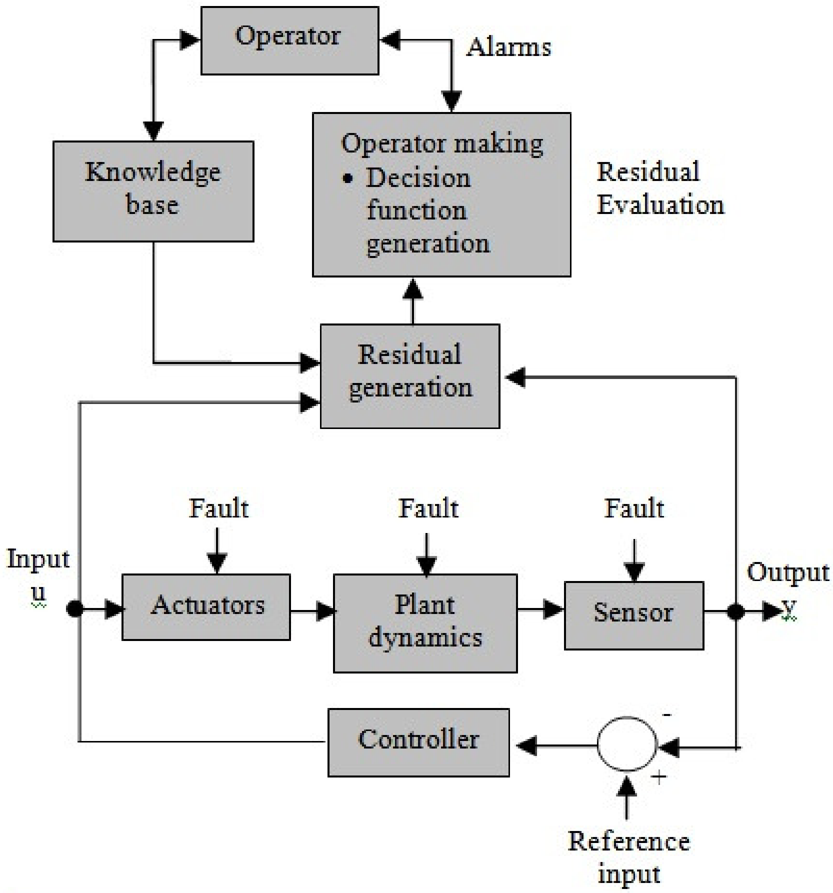


Figure-11
Residual concept in model-based fault analysis[35]

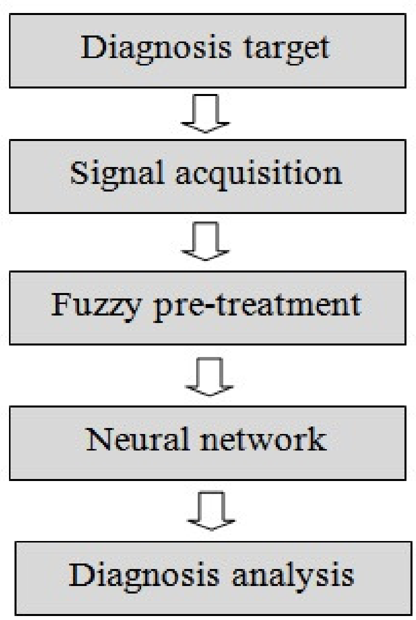


Figure-12
Phases in Neurofuzzy based fault diagnosis[36]

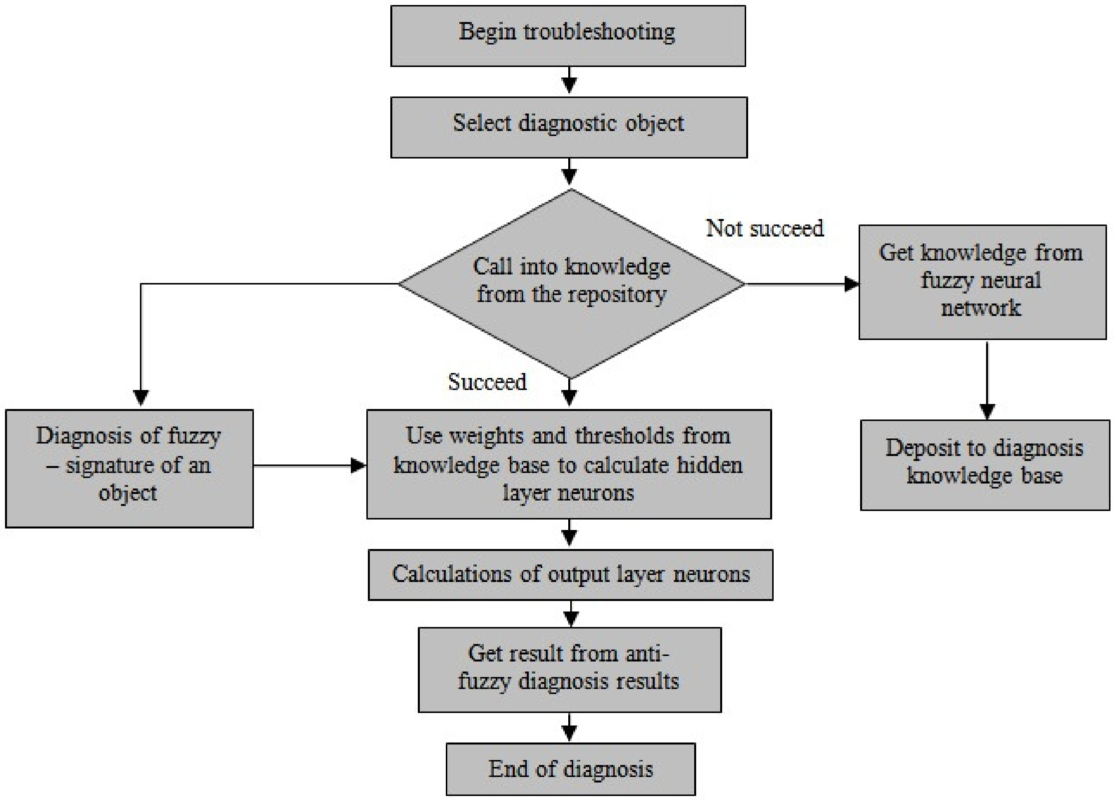


Figure-13
Flowchart of the diagnostic system troubleshooting procedure[37]

Neurofuzzy system has been widely applied in various fields of researches. In1998, Emmanouilidis, *et al.* proposed a neurofuzzy computing aided machine fault diagnosis by measuring the vibration of rotating machinery[38]. While in 2004, a study was done on the application of ANFIS technique in the fault diagnosis for voltage-fed PWM motor drive systems to detect any sudden breakdown or failure of inverters in the induction motors[39]. In 2012, a research on bearing fault diagnosis using multi-scale entropy and adaptive neuro-fuzzy inference was introduced to discover the non-linearity existing in bearing vibration and coupling effects between mechanical components within the machinery system[40]. All these researches have proven the applicability and effectiveness of neurofuzzy system to be applied in machinery fault diagnosis.

Results and Discussion

The main contribution of this neurofuzzy system in machinery fault diagnosis is to develop algorithms and adapt itself to the system behavior through the constant training of time-varying residual signals. With the increasing complexity of the current machinery system, the fault occurrence tends to become multiple simultaneous faults which are no longer easily detected by ordinary signal-based techniques such as tribology and infrared analysis. However, these growing uncertainties in fault diagnosis can be overcome by the analytical or knowledge-based neurofuzzy system due to its high learning and adaptive capability. Another strength of neurofuzzy system is that no constant human intervention is required. With the predefined rule base extracted from experts' knowledge, neurofuzzy system has the capability of further training the rules set to best suit the system behavior and monitor residual signals. With the advancement of neurofuzzy technology, techniques like ANFIS is able to define an intuitive membership function to initiate the learning algorithm and develop its own fuzzy rule base even if no prior knowledge on the system is present.

With the flexibility of neurofuzzy systems, this technique has a high potential to be applied not only in intelligent fault diagnosis but also in other engineering related domains such as medical diagnosis, pattern recognition and system modeling. An interesting study on the application of neurofuzzy systems proposed recently is the use of ANFIS based computed torque controller (type PD) in controlling puma 600 robot arm to overcome the issue of high manipulator sensitivity to uncertainties and external disturbances[41].

Conclusion

This paper reviews the hybrid technology of neurofuzzy system and its applications in machinery fault diagnosis. The important techniques include Mamdani fuzzy model, Sugeno fuzzy model and ANN as well as combining ANNs and fuzzy logics into neuro-fuzzy systems which include ARIC and NEFCON. The neurofuzzy systems have the potential to be applied in intelligent fault diagnosis where the use of fuzzy logic enables the system characteristics to be easily determined in terms of simple IF-THEN rules for easier understanding of the factors of fault occurrence. On the other hand, ANN has the capability of learning and modeling non-linear functions in industrial applications. The hybrid neurofuzzy technology is therefore combining the merits from both methods to develop a fault diagnosis technique which mimics human analyzing and reasoning skills.

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