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Condition Monitoring Leading to Control by Using Fuzzy and Hybrid Fuzzy Models: A Review

Darshan Singh, Dalveer Kaur, Yaduvir Singh

Abstract— Plant wide control is a major area of research in current days and application of artificial intelligence techniques provide better results from conventional methods in control applications. In majority of the cases, researchers got much better results when they applied artificial intelligence algorithms in various engineering problems. Engineering problems have shown remarkable enhancement in performance and also efficiency when different artificial intelligence techniques were applied in comparison to conventional techniques. There are three basic domains in artificial intelligence viz. fuzzy logic, artificial neural network and optimization techniques. This paper reports the various research contributions made into condition monitoring aspects of induction motor using fuzzy logic and neuro-fuzzy logic (hybrid fuzzy).

Keywords — Artificial Intelligence, Condition monitoring, Fuzzy logic, Neuro-fuzzy logic.

I. INTRODUCTION

From beginning artificial intelligence is widely used in various domains so as to get a better solution. In majority of the cases, researchers got much better results when they applied artificial intelligence algorithms in various engineering problems. Engineering problems have shown remarkable enhancement in performance and also efficiency when different artificial intelligence techniques were applied in comparison to conventional techniques. There are three basic domains in artificial intelligence viz. fuzzy logic, artificial neural network and optimization techniques. Fuzzy logic is a form of multi-valued logic derived from fuzzy set theory to deal with reasoning that is approximate rather than precise. In binary sets with binary logic, in contrast to fuzzy logic named also crisp logic, the variables may have a membership value of only 0 or 1. Just as in fuzzy set theory with fuzzy logic the set membership values can range (inclusively) between 0 and 1, in fuzzy logic the degree of truth of a statement can range between 0 and 1 and is not constrained to the two truth values {true (1), false (0)} as in classic predicate logic. The happy collaboration of the techniques of fuzzy logic and neural networks suggests the novel idea of transforming the burden of designing fuzzy logic systems to the training and learning of connectionist neural networks and vice-versa.

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That is, the neural networks provide connectionist structure and learning to the fuzzy logic systems and the fuzzy logic systems provide the neural networks with a structural framework with high-level fuzzy IF-THEN rule thinking and reasoning. These benefits can be witnessed by the success in applying neuro-fuzzy systems in areas like electronics component failure prediction. Artificial neural human brain. Each artificial neuron (shown as a circle) accepts several inputs, applies preset weights to each input and generates a non-linear output based on the result. The neurons are connected in layers between the inputs and outputs.The most popular neural network architecture is the multilayer perception. The network consists of an input layer, a hidden layer and an output layer. The hidden layer is used to process and connect the information from input layer to the output layer only in forward direction. The hidden layer performs feature extraction on the input data. Each neuron in the hidden layer sums up its signals after weighting them with the strengths of the respective connection and computes an output as a function of the sum. The strength of neuro-fuzzy systems involves two contradictory requirements in fuzzy modeling: interpretability versus accuracy. Fuzzy Logic is networks are modeled on the neural connections in the successfully used in today's process control systems. Fuzzy logic addresses the applications perfectly as it resembles human decision making with an ability to generate precise solutions from uncertain or approximate information. It fills an important gap in engineering design methods left by mathematical and logic-based approaches. While other approaches require accurate equations to model real-world behaviors, fuzzy design can accommodate the ambiguities of human languages and logics. It provides both an intuitive method for describing systems in human terms and automates the conversion of those systems specifications into effective models. However fuzzy logic provides heuristic reasoning. Fuzzy logic controllers with fuzzy logic support allow for thinking ahead "intelligence" to eliminate appreciable overshoots and allow for faster approach to set point and further minimizing of control fluctuations. This paper reports the various research contributions made into condition monitoring aspects of induction motor using fuzzy logic and neuro-fuzzy logic (hybrid fuzzy).

II. CONDITION MONITORING AND CONTROL

Condition monitoring of electrical machines is a challenge today. This problem has not been solved for over the decades.

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This research papers aims at collecting all such research contributions which aim at various condition monitoring aspects of induction motor using fuzzy logic and neuro fuzzy logic. Plant wide control is another major area of research in current days and application of artificial intelligence techniques provide better results from conventional methods in control applications. The first step to build an efficient fuzzy inference system is to identify the membership function from the experimental data. There is no pre defined rules for calculating number of membership functions and range of membership functions. At this point system identification comes in to act. With the help of system identification and estimation the designer can determine the number of membership functions and ranges of membership functions. After membership function is designed, rule base is created. A new fuzzy rule base can be created by neural network learning approach or else the existing rule base can be optimized by the help of evolutionary or swarm optimization techniques. Like the existing rule base optimization, the pre defined membership functions can also be optimized using evolutionary and swarm intelligence techniques. A fuzzy inference system consists of fuzzy if-then rules such as "If x1 is small and x2 is small than y is large" in MAMDANI type fuzzy inference system [11,12,13] and "If x1 is small and x2 is small than y = f(x1, x2)" in SUGENO type fuzzy inference system [14,15]. The problem with existing fuzzy rule-based systems is that the size of the rule-base (number of rules) increases exponentially with the increase in the number of fuzzy sets. This exponential increase in size of the rule-base increases the search time and hence the computation time and memory space required also increases. The membership function selection process is done with trial and error and it runs step by step which is too long in completing the problem. To minimize the computation time and memory space required different optimization techniques can be implemented in fuzzy rule base system. The optimization techniques will reduce the size of the rule base by eliminating processing unit and the computation time of the processing unit is also increased. This problem can be solved by optimizing the fuzzy rule base with the help of different optimization algorithm. Monitoring and diagnostics of electrical machines has been developing since the 1950's. Many techniques, off-line and on-line, are being used to monitor electrical machines in order to prevent catastrophic failure and minimize outages. Condition-based maintenance is also being introduced into many organizations to reduce maintenance costs by only carrying out maintenance as necessary. This requires knowledge of the condition of the electrical machines and its accessories, and the ability to predict when maintenance will be required. In operation, the electrical machines are subjected to combined stresses (electrical, thermal, mechanical and environmental), finally leading to the decrease of their life and appearance of some faults with irreversible evolution. Taking also into account the fact that most electrical machines are in operation since more than 20 years, it results the necessity of the un-necessary rules and streamlining and organizing the existing rules. A fuzzy inference system consists of IF-THEN rules. The major problem of fuzzy rule base is that, with the increase in number of membership functions, there is an exponential rise in the number of rules. The exponential rise in number of rules increases the memory requirement of the fitting out the electrical machines with systems for monitoring and diagnosing their condition. Condition Based Maintenance (CBM) is an advanced maintenance policy developed in recent years. CBM is mainly based on the condition information obtained from equipments, it uses those information by the data analysis and diagnostic techniques to forecast the residual life of equipments or failure rate, then makes decisions to equipment maintenance by optimizing their reliability index, namely whether the equipment need prevention maintenance, if needed, when the equipment should be repaired. This idea has been widely accepted in the field of maintenance, the current urgent problem needed to solve is how to use the condition information in the process of the scientific decision-making for device maintenance. The initial CBM decision-making depends on the measure and test of condition signal of devices. When the monitored value exceeds the threshold or the trend occurs to change, the maintenance decision should be timely decided according to pre-set threshold value. This maintenance policy is easy and simple, but for a system with multiple state variables tested it is difficult to reflect the combined effect on a variety of factors. Therefore, the key of CBM decision-making is to establish a precise and reasonable functional relation between their health levels and their condition parameters. Various condition monitoring techniques under development are as follows:

A. On-line Winding Movement Detection by FRA Method

The conventional FRA test requires electrical machines outage to carry out the test. On-line FRA could reduce or eliminate the need for outages to carry out an FRA test. Work has been done on developing on-line FRA measurement [12].

B. Fibre Optic System Temperature Measurement

The traditional method to measure temperature of electrical machines is to measure the top and bottom oil temperature of the electrical machines and estimate the hot spot temperature. New equipment has been developed that is able to monitor the temperature by two different ways. One is a distributed measurement along the entire length of the winding by a fibre optic cable. The other is a point measurement at the hot spot. The temperature of the complete winding could be monitored if a fibre optic cable can be laid along the electrical machines winding during construction of the electrical machines. This would be a very useful tool for monitoring the internal electrical machines condition. However, there are drawbacks of this method. High cost and high mechanical stresses on the fibre (squeezing and buckling) are a major concern. The optical fibre needs to be handled with extreme care. It would have to be installed during electrical machines construction. The application of the fibre optic sensor so far has been mainly for laboratory research and principle design [46].

C. Techniques for Partial Discharge Detection

Techniques using detection of ultra high frequency signals have been applied to electrical machines. The work shows some promise for partial discharge detection in electrical machines. Investigations are also proceeding on improving acoustic detection of partial discharge as well as further work on electrical detection for in service monitoring. The goal is to be able to detect and ideally located partial discharge levels with a minimum sensitivity of at least 100 pC [26].

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D. Ultrasonic Emission Detection

The ultrasonic emission detection can be generated by ionization attributed to electric field distortion caused either by external contamination or by internal partial discharges. This method takes advantage of ultrasound propagation (20 kHz and above) to detect ionization, corona effect and arcing. Figure 7 shows application of this method to CT on-line evaluation [74].

Figure 1: On-line ultrasonic emission detection using an ultrasonic shotgun

E. Vibration Detection Development

Some research work has been focussed on using electrical machines vibration signal to detect winding looseness and on developing the analysis technique for interpreting the vibration data. The method is based upon- to look for the changes in the electrical machines vibration signature to detect movement in the electrical machines winding [19].

F. Diagnostic Software and Expert Systems

Diagnostic software, which gives more definite indication of the electrical machines problems than conventional analysis, is under investigation by many researchers and utilities [40]. A great deal of research work has been done on software to interpret electrical machines oil test data such as gas, moisture content and dielectric strength and correlating the data with the electrical machines insulation condition. Expert systems have been developed that give an alarm signal to system operators [9].

III. FUZZY LOGIC AND HYBRID FUZZY LOGIC MODEL DEVELOPMENT

There is a wide variety of engineering application. These algorithms and their techniques have been applied to almost every engineering discipline. Presently, these techniques are applied on data mining, image processing, bio informatics, digital signal processing, and measurement of concrete beams, vibration analysis, machine vision, machine control, and navigation and communication equipment. And when linguistic variables are used, these degrees may be managed by specific functions. A fuzzy logic approach may help to diagnose induction motor faults. In fact, fuzzy logic is reminiscent of human thinking processes and natural language enabling decisions to be made based on vague information [2]. Figure 2 shows a Fuzzy Logic model which has been developed in MATLAB in this case.

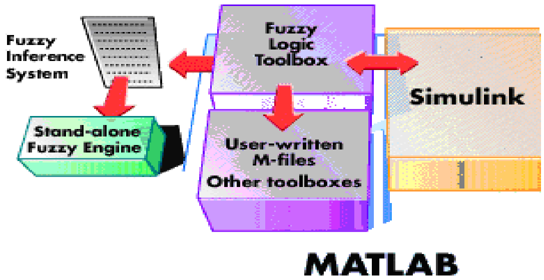

Figure 2: Fuzzy Logic implementation in MATLAB

Fuzzy logic allows items to be described as having a certain membership degree in a set. This allows a computer, which is normally constrained to 1 and 0, to delve into the continuous realm. When conducting fault diagnosis, there are several situations in which an object is not obviously “good” or “bad”, but may fall into some interior range [3]. According to the fact that induction motor condition interpretation is a fuzzy concept, during the past few years, researchers have proposed some fuzzy logic based diagnosis approaches. A major difficulty is the lack of a well processing of fuzzy input data. This thesis will aim at applying fuzzy logic to the diagnosis of induction motor based on the amplitude features of stator currents. This method has been chosen because fuzzy logic has proven ability in mimicking human decisions and the stator voltage and phase condition monitoring problem has typically been solved. The motor condition is described using linguistic variables. Fuzzy subsets and the corresponding membership functions describe stator current amplitudes. A knowledge base, comprising rule and databases, is built to support the fuzzy inference. The induction motor condition will be diagnosed using a compositional rule of fuzzy inference. Model validation is the process by which the input vectors from input/output data sets on which the FIS was not trained, are presented to the trained FIS model, to see how well the FIS model predicts the corresponding data set output values. We use a validation data set to check and control the potential for the model over fitting the data. One problem with model validation for models constructed using adaptive techniques is selecting a data set that is both representative of the data the trained model is intended to emulate, yet sufficiently distinct from the training data set so as not to render the validation process trivial. If we have collected a large amount of data, hopefully this data contains all the necessary representative features, so the process of selecting a data set for checking or testing purposes is made easier. However, if we expect to be presenting noisy measurements to our model, it is possible the training data set does not include all of the representative features we want to model. The basic idea behind using a checking data set for model validation is that after a certain point in the training, the model begins over fitting the training data set. In principle, the model error for the checking data set tends to decrease as the training takes place up to the point that over fitting begins, and then the model error for the checking data suddenly increases.The happy collaboration of the techniques of fuzzy logic and neural networks suggests the novel idea of transforming the burden of designing fuzzy logic systems to the training and learning of connectionist neural networks and vice-versa.

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That is, the neural networks provide connectionist structure and learning to the fuzzy logic systems and the fuzzy logic systems provide the neural networks with a structural framework with high-level fuzzy IF-THEN rule thinking and reasoning. These benefits can be witnessed by the success in applying neuro-fuzzy systems in areas like electronics component failure prediction [4]. In fuzzy logic, all data are shown as values between 0 and 1. The information in fuzzy logic is verbal, such as "big," "small," "more," or " few." The fuzzy implication process is conducted according to rules that are defined between the verbal expressions. Every logical system can be defined as fuzzy. Fuzzy logic is very suitable for systems whose mathematical models are hard to develop. Fuzzy logic has the ability of processing uncertain or incomplete information. The FLC is shown in Figure 3.

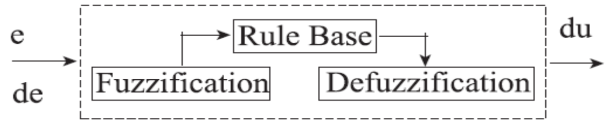

Figure 3: Basic configuration of FLC

As shown in Figure 4.1, the FLC system consists of 3 components. These are fuzzification, the rule base, and defuzzification. Fuzzification, the first component of the FLC, converts the exact inputs to fuzzy values. These fuzzy values are sent to the rule-base unit and processed with fuzzy rules, and then these derived fuzzy values are sent to the defuzzification unit. In this unit, the fuzzy results are converted to exact values. The FLC' s input values are generally the control error and the variation of this error in one sampling time. According to these variables, a rule table is produced in the FLC' s rule-base unit. The holding of the voltage and the amplitude of the load at the desired values of 380 V and 50 Hz is done by the FLC. The 3-phase voltage is transferred from the a-b-c axes to the d-q axes first. The voltage divides into its components, which are controlled separately. At the output of the control, the voltage is transferred in reverse, from the d-q axes to the a-b-c axes, and, at the end, the PWM is driven by that voltage. These controls are done in the regulator block. In Figures 4.2 and 4.3, the error and the error variation of the input data of the FLC' s input variables are shown. Triangle membership functions were used. These functions are called NB, NK, S, PK, and PB, and the data vary between －1 and 1, as seen in the Figures 4.

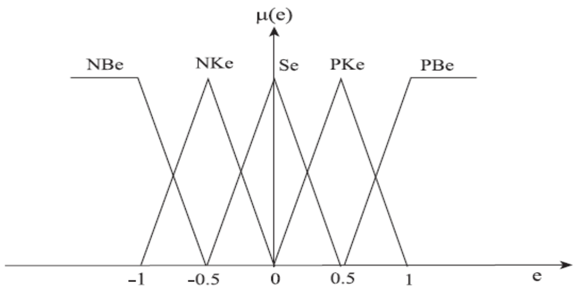

Figure 4: Error membership functions

The triangle membership function is defined in Eq. (1), below.

$$\mu_{MU}(x) = \max\left(\min\left(\frac{x-x_1}{x_T-x_1}, \frac{x_2-x_1}{x_2-x_T}\right), 0\right) \qquad (1)$$

Fuzzy models are flexible mathematical structures that, in analogy to neural networks and radial basis functions, have been recognized as universal function approximations. Fuzzy models use 'If-Then' rules and logical connectives to establish relations between the variables defined for the model of the system. For the given example, let the system to model be the relation between the noise sensation and the sound pressure level. Thus, in fuzzy modeling the fuzzy 'If-Then' rules take the form. The fuzzy sets in the rules serve as an interface amongst qualitative variables in the model, and the input and output numerical variables. The fuzzy modeling approach has several advantages when compared to other nonlinear modeling techniques, such as neural networks: in general, fuzzy models can provide a more transparent representation of the system under study, maintaining a high degree of accuracy. Fuzzy controllers tuning implies the handling of a great quantity of variables like: the shape, number and ranges of the membership functions, the percentage of overlap among them and the design of the rule base. The problem is more complicated when it is necessary to control multivariable systems due that the number of parameters. The importance of the tuning problem implies to obtain fuzzy system that decrease the settling time of the processes in which it is applied, or in some cases, the settling time must be fixed to some specific value. In this work a very simple algorithm is presented for the tuning of a fuzzy controller using only one variable to adjust the performance of the system. The results would be obtained considering the relationship that exists between the membership functions and the settling time. Fuzzy rule-based systems include many aspects of fuzzified values, such as the rules antecedents and consequence. The rules structure are usually of the form IF THEN. Fuzzy logic models can be developed from expert knowledge or from process (patient) input-output data. Figure 5 below shows fuzzy logic implementation steps.

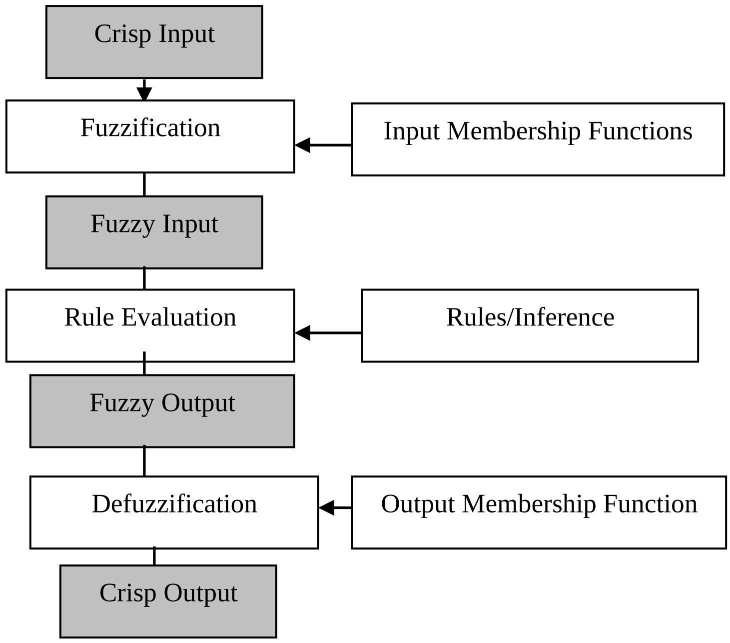

Figure 5: Fuzzy Logic Model

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In the field of artificial intelligence, Neuro-fuzzy refers to combinations of artificial neural networks and fuzzy logic. Neuro-fuzzy was proposed by J. S. Jang [5,6,7].

Neuro-fuzzy hybridization results in a hybrid intelligent system that synergizes these two techniques by combining the human-like reasoning style of fuzzy systems with the learning and connectionist structure of neural networks. Neuro-fuzzy hybridization is widely termed as Fuzzy Neural Network (FNN) or Neuro-Fuzzy System (NFS) in the literature. Neuro-fuzzy system (the more popular term is used henceforth) incorporates the human-like reasoning style of fuzzy systems through the use of fuzzy sets and a linguistic model consisting of a set of IF-THEN fuzzy rules. The main strength of neuro-fuzzy systems is that they are universal approximators with the ability to solicit interpretable IF-THEN rules. Figure 6 shows a neural network which is used for intelligent inferencing.

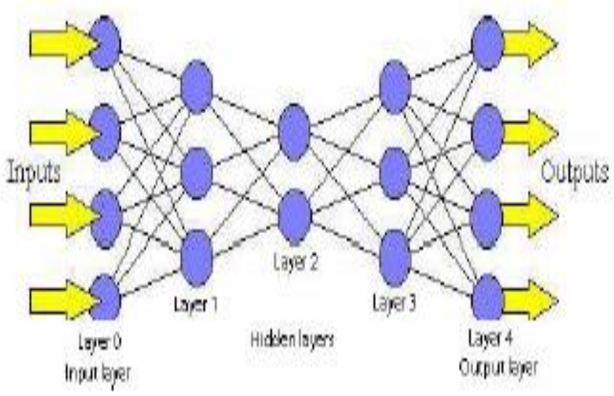

Figure 6: Neural network

Artificial neural networks are modeled on the neural connections in the human brain. Each artificial neuron (shown as a circle) accepts several inputs, applies preset weights to each input and generates a non-linear output based on the result. The neurons are connected in layers between the inputs and outputs. The most popular neural network architecture is the multilayer perception. The network consists of an input layer, a hidden layer and an output layer. The hidden layer is used to process and connect the information from input layer to the output layer only in forward direction. The hidden layer performs feature extraction on the input data. Each neuron in the hidden layer sums up its signals after weighting them with the strengths of the respective connection and computes an output as a function of the sum [8, 9,10].

The strength of neuro-fuzzy systems involves two contradictory requirements in fuzzy modeling: interpretability versus accuracy. In practice, one of the two properties prevails. The neuro-fuzzy in fuzzy modeling research field is divided into two areas: linguistic fuzzy modeling that is focused on interpretability, mainly the Mamdani model [11,12,13]; and precise fuzzy modeling that is focused on accuracy, mainly the Takagi-Sugeno-Kang (TSK) model [14,15]. The "POPFNN" architecture is a five-layer neural network where the layers from 1 to 5 are called: input linguistic layer, condition layer, rule layer, consequent layer and output linguistic layer. The fuzzification of the inputs and the defuzzification of the outputs are respectively performed by the input linguistic and output linguistic layers while the fuzzy inference is collectively performed by the rule, condition and consequence layers. Various fuzzy membership generation algorithms can be used: Learning Vector Quantization (LVQ), Fuzzy Kohonen Partitioning (FKP) or Discrete Incremental Clustering (DIC). Generally, the POP algorithm and its variant LazyPOP are used to identify the fuzzy rules. Fuzzy Logic model tuning implies the handling of a great quantity of variables like: the shape, number and ranges of the membership functions, the percentage of overlap among them and the design of the rule base. The problem is more complicated when it is necessary to control multivariable systems due that the number of parameters. The importance of the tuning problem implies to obtain fuzzy system that decrease the settling time of the processes in which it is applied, or in some cases, the settling time must be fixed to some specific value.

Kong and B. Kosko introduce the concept of FAM - fuzzy associative memory. It is based on his view of fuzzy state space as a hyperbolic unit cube. FAMs map input 'balls' to output 'balls'. The balls are clusters of data in the state space associated with certain conditions. Adaptive fuzzy associative memories, AFAM, change over time as new data is sampled and processed. Kosko uses his FAM concept to build on the work of Nguyen and Widrow by designing a fuzzy truck backer-upper [16]. His fuzzy controller consistently chooses a smooth path to its final destination. Kosko points to the fact that Nguyen and widrow's neural controller did not always converge. He also points out that the fuzzy controller did not require 20,000 iterations for training. Training was achieved by encoding "common sense" FAM rules.

H Berenji, Y Chen, C Lee, S Murugesan, and Jang perform experiments with fuzzy control and a cart-pole balancing problem [17]. In their comparison of the fuzzy logic controller and a state-feedback controller, the fuzzy logic controller scored high marks in the areas of ease of implementation, robustness and percentage overshoot. The state feedback controller had better settling times and ease of modification. They felt that the largest limitation of the fuzzy method is in the calibration of the membership functions. They suggest research in the area of "automatic learning of approximate control rules." W Z Qioa, W P Zhuang, T H Heng, and S S Shan design a Rule Self-regulating Fuzzy Controller (RSFC) [18]. They are interested in adjusting a fuzzy rule base on-line in real-time. In order to give the system the ability to quickly modify the fuzzy controller's rule base, the authors use a special type of rule base which is more easily modified. The example given is that of a fuzzy logic controller adjusting the proportional and integral gain constants in a simple feedback control system. C C Jou and N C Wang present their work in the area of adaptive fuzzy logic systems [19]. Error back propagation is applied to a fuzzy logic system to adjust the rule base according to a pre-specified training set. The specific application addressed is that of backing up a truck to a dock. The researcher's system performed as well as the neural network controller of Nguyen and Widrow, but required far fewer training sessions. They note that in order to develop a rule base capable of generalization, training samples that are "homogeneously distributed throughout the entire state space" are necessary.

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D Nguyen and B Widrow use two neural networks to control a truck and trailer as it backs up to a dock from any initial position [20]. The first neural network, called an emulator, learns to identify the system's dynamic characteristics. The second provides the actual control. After 20,000 simulated backups, the controller is able to move the truck to within 3% of the desired position. The network also develops a control strategy, as demonstrated by the fact that initial moves sometimes increase the current error in order to prepare the truck and trailer for ultimate success. A Guez, J Eilbert, and M Kam propose architecture for neural network control that can serve as an adaptive control system [21]. A comparison is made to traditional model reference adaptive control (MRAC). In their example of a robotic manipulator, the neural network approach shows significant improvement in performance over the MRAC. The neuro-controller is more general, making it possible to be trained for many problems. It shows the most improvement over MRAC as the system increased in order. It is also more stable and less sensitive to plant dynamics.

D Psaltis, A Sideris, and A Yamamura address the problem of training a neuro controller over a large state space [22]. They suggest training the neural net in two modes – generalized training and specialized training. The generalized training session extracts the major features. The specialized training works to define detailed boundaries between samples. This decreases the iterations necessary to train the neuro-controller and provides better response in important operating regions. Newton R T and Y Xu outline the work being done at Carnegie Mellon University in the area of neural network control of a robotic arm [23]. A seven degree-of-freedom space manipulator is controlled with a neural network resulting in 85% less trajectory error than recorded under PID control. The neural network is trained on-line and made use of a moving average feedback. The feedback provides the network with the ability to plan current control based on both the current input and the recent response of the network to past inputs.

Arai F, Rong L, and Fukuda T. use neural networks to control a three link robotic arm that is manipulating a flexible plate [24]. The problem is complicated by the fact that the control must take into account not only the trajectory planning, but also the vibration of the flexible material being held. Four neural networks are used to learn the error caused by the vibrations of the flexible plate. The networks have 4, 10, and 1 nodes in the input, hidden and output layers, respectively. After training, the model of the system's error, contained in the neural networks, is used to improve control. Liu S and Asada H describe a neural network control of a deburring robot [25]. Initially, a neural network is trained off-line to data obtained by recording a human's control of the robot. This training data teaches general control strategy and task planning. The final control system also makes neural network adjustments on-line based on data acquired during operation. This training fine tunes precise controlled motion. Because of this second learning capability, the neural network controller was able to exceed the performance of the human controller.

T. C. Hsia and Z. Mao propose a scheme for obstacle avoidance of redundant manipulators by neural network [26]. Their scheme, called q-system, translates a desired Cartesian coordinate position, Xd, into four joint angles, q. The training samples are taken from known solutions given by the forward kinematics solution. In this manner, a neural network was trained for the inverse kinematics solution of a four-link arm. The system is improved by performing a coordinate transformation of q, which localizes the search for an inverse solution.

J Cooperstock and E Milios incorporate neural network control into a vision guided robotic arm [27]. Neural networks take the place of complex numerical solution techniques for both the solution of the inverse kinematics of the arm and for the solution of the perspective projection of the stereo vision system. Cooperstock and Milios's controller is comprised of five neural networks. The networks specialize in the operations of approaching, centering, paralleling, reaching, and adjusting. The researchers describe their control system as being competitive with traditional systems.

J D Yegerlehner and P H Meckl utilize the learning capabilities of neural networks to adapt the control of a robot experiencing large changes in payload weight [28]. One neural network is trained for the inverse kinematics, while another is trained to estimate the mass of the payload. The authors reveal that the artificial neural network did not model the inverse kinematics as well as a comparison model of least squares fitting parameters. They point to the fact that the network inputs were only the joint angles and their two time derivatives. They suggest that a "richer set of inputs" would be necessary for improving performance.

Nauck, Klawonn, and Kruse research the fusing of neural networks and fuzzy systems in an attempt to overcome the disadvantages expressed by other researchers using only one of the technologies [29]. Their inverted pendulum application is similar to Berenji's, et al. The researchers' "neural network oriented fuzzy control" system adjusts its fuzzy set definitions. The application of this system to an inverted pendulum was able to balance the pendulum and reduce the rules required from 512 to fewer than 40. Not only did learning take place, as in a neural network, but the resulting system was defined in the linguistic variables. J S Jang designs a self-learning fuzzy controller based on temporal back propagation [30]. The current state of the system is compared to the desired state and the error is back propagated through the system to adjust individual fuzzy parameters. Tests on an inverted pendulum show that significant adjustments were made on membership function definitions. The trained system exhibited robustness and fault tolerance. Archer N P and Wang S. propose a method for using neural networks to define membership functions [31]. Their algorithm incorporates what they term as a Fuzzy Membership Model. Neural networks are used to learn how to classify patterns that fall near regions of uncertainty in pattern space. In their example, one neural network is used to learn the sharp boundary between two classes, while two other neural networks are trained to determine a pattern's fuzzy membership in a particular class.

Berenji H R and Khedkar P. also use neural networks to define fuzzy membership functions [32]. They emphasize the importance of selecting the correct granularity for describing the values of each linguistic variable. Berenji and Khedkar implement a generalized approximate-reasoning-based intelligent control (GARIC). One neural network is used to evaluate the performance of the fuzzy system.

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One neural network is used to adjust the membership function based on the evaluation network's output. Simulations for the classical cart-pole balancing problem are performed. A Blanco and M Delgado present their work in the area of neuro-fuzzy techniques [33]. They suggest that a neural network's strength lies in its ability to approximate a function from sample data. The parallel in fuzzy system applications would be the need to infer an output from a predefined rule base. Blanco and Delgado suggest training neural networks to the knowledge contained in a fuzzy rule base. The neural networks can then be used in the place of a rule base.

J M Keller, R R Yager and H Tahani justify this approach by pointing to the fact that in fuzzy logic systems "as the number of antecedents' clauses increases, the storage and the computation in the inference process grow exponentially" [34]. Their research indicates that for complex systems, a fuzzy rule base is more efficiently stored in a neural network. Also, due to the parallel nature of a neural network, the inference procedure would require less time in a parallel implementation.

W. Pedrycz takes a similar approach to combining neural networks and fuzzy logic [35]. His approach, however, does not involve training a generic neural network to emulate a rule base. He introduces two new classes of fuzzy neurons. The aggregative neurons realize AND, OR, and mixed AND/OR operations. The referential neurons realize binary relations of matching, difference, inclusion and dominance. The fuzzy rule base is "encoded" into a neural network by appropriate architecture design and weight selection using these two types of fuzzy neurons.

S Rahman outlines his use of neuro-fuzzy technology in a practical, home appliance problem [36]. The problem is that a toaster's darkness setting does not take into account the initial temperature of the toaster. Rahman equips a toaster with a temperature sensor and microcontroller. The temperature is read by an eight bit microcontroller that controls the toaster coils. Data was collected off-line and used by a neural network to derive 52 rules and 3 membership functions. After training, the toaster produced toast with almost identical degrees of darkness regardless of the initial temperature of the toaster.

R Lea, Y Jani, and H Berenji explore the use of neuro-fuzzy control for space shuttle rendezvous and docking [37]. An architecture composed of two networks is used. The two networks are referred to as the evaluation network and the action network. The evaluation network is a multilayer back propagation neural network dedicated to the "if" side of a fuzzy rule base. Similarly, the action network is dedicated to the "then" side of the rule base.

S C Lee and E T Lee introduce the fuzzy neuron [38]. The fuzzy neuron incorporates fuzzy logic into the neurons of the neural networks. Their approach is based on the fact that the original neuron model proposed by McCulloch and Pitts produced an all-or-none output [39]. It was quickly realized that neurons with output in the range of [0, 1] produced much better results. The authors say that their fuzzy neurons are best used in areas of "soft sciences, such as in prediction making, pattern recognition, and decision making processes.W. Pedrycz successfully trained a fuzzy-neuron neural network to control a system with two state variables and two control variables [40]. His approach attaches linguistic terms in the place of numeric weights between the individual processing elements. This makes it easier to interpret what goes on in the network. Pedrycz also points out that fuzzy-neuron controllers make it easier to understand and adjust the trade-off between information granularity and learning capabilities.

J M Keller and D T Hunt address the problem of a neural network classifier's inability to terminate training when training samples from two classes are non-separable [41]. They suggest that training samples that are non-separable are probably atypical of their respective class. Fuzzy techniques can be incorporated into the perceptron model to put less weight on these atypical samples during training. The researchers respond to the rhetorical question, "Why not just identify the atypical vectors and ignore them?" By making a sample vector's influence during training dependent on how closely it represents its class, the boundaries between the classes can be better characterized than if vectors are ignored.

IV. DISCUSSIONS

The use of neural networks, fuzzy logic and neuro-fuzzy technology in control has progressed in that order. Neural networks and fuzzy logic, used independently, have both demonstrated their value in control systems. More recently, neuro-fuzzy control has brought even more improvement to the quality of intelligent control. The following is a survey of the research done in the areas of intelligent control, followed by a survey of condition monitoring area. Neuro-fuzzy approach combines two powerful computing disciplines: Adaptive neural networks and fuzzy set theory. Neural networks are well known for its ability to learn and adapt to unknown or changing environment to achieve better performance. Fuzzy set theory, on the other hand, can by its effectiveness in handling linguistic information, incorporate human knowledge, deal with imprecision and uncertainty, and clarify the relation between input and output variables. A neuro-fuzzy can be used to study both neural as well as fuzzy logic systems. A neural network can approximate a function, but it is impossible to interpret the result in terms of natural language. The fusion of neural networks and fuzzy logic in neuro fuzzy models provide learning as well as readability. Control engineers find this useful, because the models can be interpreted and supplemented by process operators. Recently, the combination of neural networks and fuzzy logic has received attention. The idea is to lose the disadvantages of the two and gain the advantages of both. Neural networks bring into this union the ability to learn.

V. CONCLUSIONS

Fuzzy logic brings into this union a model of the system based on membership functions and a rule base. This field of study is still in its infancy. Universally accepted techniques and a general consensus on the direction of research have not yet been established. Most of the work done in this area is still associated with individual researchers and has not been adopted as standard strategy. Determining the fuzzy membership functions from sample data using a neural network is the most obvious method of using the two together. The definition of the membership function has a huge impact on the system response. Often, the programmer must use trial and error to find acceptable values.

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There is lot of scope to work on plat wide control. Plant wide control is used in the practice. Fuzzy models and hybrid fuzzy models have demonstrated their technical superiority in many areas and applications. As can be seen in the literature, no where fuzzy and various hybrid fuzzy logic models have been developed for the plant wide control.

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