A Fuzzy Neural Network Fault Diagnostic System

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ABSTRACT
Fault diagnosis of the modern complex devices is one of the most important tasks in many application areas. Recently, it is found that, neural networks and fuzzy logic control have widely used for the diagnostic devices. Fuzzy logic systems provide high processing speed but lower computing power. While, the neural networks can achieve high computing power but slower convergence rate. Therefore, the proposed system introduces the fuzzy neural network fault diagnostic system for diagnosis the complex devices. The integration between the fuzzy logic and the neural network enables the diagnostic system to have the advantages of both of these techniques and overcome the limitations of each of them. The suggested system has been applied for diagnosis a production line of radiated surgery tools as a non-linear complex faulty system. The obtained results show that the proposed diagnostic system can diagnose the complex devices with more accurate and speedy results rather than the traditional diagnostic system. Therefore, it can be applied for the practical applications effectively.

Keywords
Fault diagnosis, Fuzzy Logic, Neural Network

1. INTRODUCTION
Fault diagnosis of the production lines for radiating the surgery tools are very important task for the disinfection process in the medical and health-care fields. The surgery tools must be radiated with suitable determined accurate doses. The lower or higher doses can cause great problems and risks for the surgery operations. Recently, the development of automation, integration and intelligence structure of these production lines is become complex devices. When a failure appeared in this production line, it is very dangerous and difficult to control the radiation dose for the surgery tools.

The proposed system introduces a new automatic diagnostic system that is used to diagnose the production lines for the radiated surgery tools. It integrates the fuzzy logic and the neural network to have the power of these techniques and overcome their drawbacks. Thus, it is found that, the fuzzy logic control systems provide high processing speed but lower computing power. On the other hand, the neural networks can achieve high computing power but slower convergence rate.

The reminder of this paper is organized as: Section 2 represents an overview of the fuzzy logic. Section 3 introduces the neural networks. Section 4 deals with the proposed system and its applicability for the production line for the radiated surgery tools. Section 5 represents the obtained results and the conclusion is presented in section 6.

2. FUZZY NEURAL NETWORK SYSTEMS
In Natural, Neural network (NN) consists of an interconnected group of neurons. Artificial Neural Network (ANN) is made up of interconnecting artificial neurons (Programming constructs that mimic the properties of biological neurons). A Neural Network is an analog and parallel computing system. It is made up of a number of very simple processing elements that communicate through a rich set of interconnections with variable weights or strength. ANN (subsequently referred to as NN) is used in solving artificial intelligence problems without creating a model of a real biological system. NN processes information using connectionist approach to computation [1]. It changes it structures based on internal or external information that flows through the network during the learning phase. NN can be used to model complex relationship between input and output or find patterns in data [2]. A simple NN which comprises of three layers (Input, Hidden and Output layers) as shown in fig. (1).

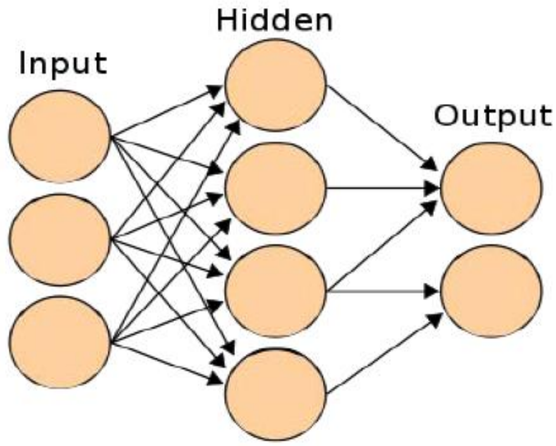

Fig. (1): A simple Neural Network

A layer of “input” connected to a layer of “hidden” units, which is in turn connected to a layer of “output” units. The activity of the input unit represents the raw information that is fed into the network; the activity of the hidden units is determined by the activity of the input unit and the weights between the hidden and output units. The hidden units are free to construct their own representation of the input; the weights between the input and hidden units determine when each hidden unit is active, and so by modifying these weights, a hidden unit can choose what it represents [3]. NN employs learning paradigm that includes supervised, unsupervised and reinforcement learning. But, NN cannot handle linguistic information and also cannot manage imprecise or vague information [4].

Fuzzy Logic (FL) provides a method of modeling imprecise models of reasoning, such as common sense reasoning, for uncertain and complex processes. Fuzzy set theory resembles human reasoning in its use of approximate information and uncertainty to generate decisions. The ability of fuzzy logic to approximate human reasoning is a motivation for considering fuzzy systems in this work. In fuzzy systems the evaluation of the output is performed by a computing framework called the *fuzzy inference system*.

A fuzzy inference system is a function/model that takes a fuzzy set as an input and performs a composition to arrive at the output based on the concepts of fuzzy set theory, fuzzy *if-then* rules and fuzzy reasoning. Fuzzy inference involves: the fuzzification of the input variables, evaluation of rules, aggregation of the rule outputs and finally the defuzzification of the result. There are two popular types of fuzzy models: the Mamdani model and the Takagi-Sugeno model. The Takagi-Sugeno model is popular when it comes to data-driven identification [5].

Recently, researchers concern the development of fuzzy-neural network system is a learning machine that finds the parameters of a fuzzy system (i.e., fuzzy sets, fuzzy rules) by exploiting approximation techniques from neural networks [6]. Fuzzy-Neural Network system refers to the combination of artificial neural network and fuzzy logic. It eliminates the individual weaknesses of neural network and fuzzy logic while making use of their best advantages [7,8].

Figure (2) represents the structure of Fuzzy-Neural Network where X_i are input variables and f_n are output fault vectors. $\mu_i^j (i, j = 1, 2, \dots, n)$ are degrees of membership, i represents the i-th variable of input, j represents fuzzy division number of corresponding variables. IW and LW are the connecting weights of hidden layer and the connecting weights of output layer respectively. The back-propagation training algorithm is used for training the neural network.

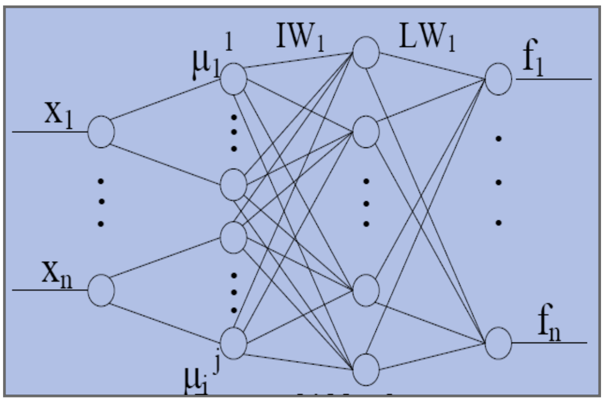

Fig. (2): Structure of Fuzzy-Neural Network

However, the proposed system can integrate the fuzzy logic and the neural networks for a general fault diagnostic system to deal with the complex and critical systems. It can introduce the decomposing of the neural network into sub-network to enable the diagnostic system to diagnose the complex devices.

3. PROPOSED FAULT DIAGNOSTIC SYSTEM FOR AN AUTOMATIC PRODUCTION LINE

The proposed fault diagnostic system is one of the fuzzy-neural network systems. It introduces the integration between the neural network and the fuzzy logic control for complex and critical systems. It can collect the advantages of using the uncertain fuzzy logic information, and the self-learning and adaptation characteristics of neural network. It can divide the structure of the neural network into group of sub-networks each of them can deal with a single fault. So, the proposed system can overcome the complexity of diagnosis the non-linear faults and diagnose parallel faults, scale-up the size of the complex devices to be diagnosed and speed up the diagnostic operation. It has been applied for diagnosis the production line that used for radiating the surgery tools.

The flowchart of the proposed fuzzy neural network fault diagnosis is shown in fig. (3) that is illustrated as follows:

1) Working condition data is collected when fault system is running. Symptom parameters are extracted and normalized.

2) Convert the symptom parameters normalized into fuzzy sets which are represented by membership.

3) Using the data fuzzed as input parameters of sub-neural networks, fault causes (diagnosis) are reasoned from fault Symptoms using the Back Propagation-Neural Network algorithm that is the training algorithm for all the sub-neural networks [9].

4) Based on outputs of network, fuzzy membership vectors of fault causes are obtained. The types of fault causes are determined by analyzing the vectors.

The operation of proposed system can be summarized in two steps: The first step: extraction of fault symptoms. It means data extraction and normalization. The second step: feeding the normalized data for the sub-neural networks (that are used to manage the complexity of the diagnostic process) and continuous mapping of fault symptom vector X and fault reason vector F till determine the required diagnosis.

The fuzzy logic is applied for the faults that cannot be represented in the form of two-valued [0,1]. The specific number of fuzzy subsets of fault symptom inputs is determined by practical situation.

When applying the proposed fuzzy-neural network fault diagnostic system for the production line that used in radiating the surgery tools. It has two main functions: acquiring fault information real-time online and determine the causes of the faults automatically. So, it has full using of acquiring field fault information to determine fault causes and fault position rapidly.

The first step of the proposed system is extracting the needed information from the knowledge of the domain' problem that in our case a production line of the radiated surgery tools. The main types of the faults of this system can be summarized as: sensor faults, actuator faults, control unit faults and the symptoms of the input and output signals.

Sensor faults: frequency signal sensor faults (such as speed sensor, engine speed sensor, input axis speed sensor); analogue signal sensor faults (such as throttle opening sensor, clutch engaging sensor, choosing position sensor and shift position sensor); switching signal sensor faults (such as all kinds of on-off switch). Actuator faults (such as choosing motor fault, shifting motor fault, clutch motor fault). Control unit faults: (such as power supply fault and driving chips fault). While, the inputs' faults can be classified as analog and frequency signals.

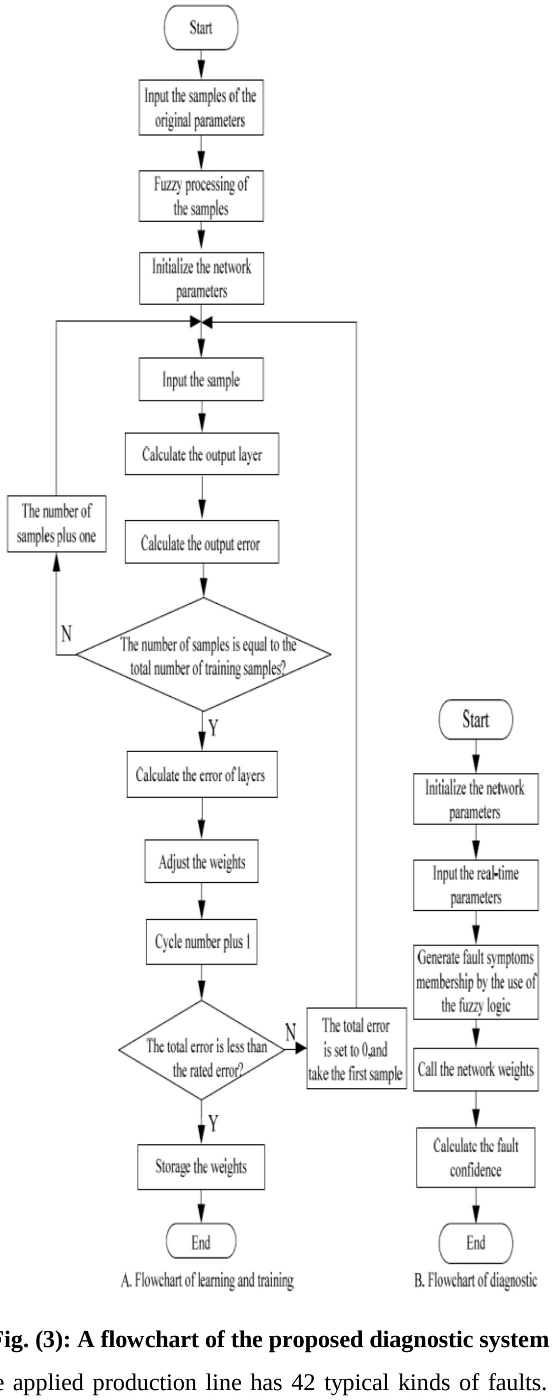

Fig. (3): A flowchart of the proposed diagnostic system

The applied production line has 42 typical kinds of faults. If they are designed as a single neural network, the network structure and the training samples will be large, which may make difficult for the network training. At the same time the network is sensitive to the sample error, and it's easy to cause low classification accuracy, which will make inaccurate results for the fault diagnosis. These challenges cause great problem for any traditional fuzzy-neural network diagnostic systems. Therefore, the proposed system can overcome these limitations by decomposing the neural network into multiple sub-networks based on the operation methods and fault characteristics of the production line, each fault is related to certain fault symptoms (real-time monitoring parameters). Each fault and propagated effect can be mapped with an independent sub network. According to the real-time running parameters collected at the input, the sub-networks related to these symptoms are activated till achieve the required diagnosis.

The inputs of the sub-network are considered the symptom of the fault, and the output is the level of confidence for the fault. The use of the parallel sub-network structure can reduce input and output nodes of the network, accelerate the speed of fault diagnosis and can achieve the simultaneous diagnosis of multiple faults. At the same time, each sub-network is trained independently and without mutual influence. Sub-network problems will not affect the other sub-network, and easy to modify and supplement of the network.

On the other hand, fuzzy logic control can deal with the uncertain values of the parameters and drive the adapted weights for the neural network to automate the self-learning of the neural network. The fuzzy logic can obtain the membership grades of faults for every circuit based on the broken-down degree of operation and orders the sequence of this membership grades. The priority of diagnosis is consistent with the sequence. When the membership grade of fault is smaller than a threshold, the circuit is considered free of the faults.

4. EVALUATION OF THE PROPOSED SYSTEM

To evaluate the proposed fuzzy- neural network fault diagnostic system, it has been applied for diagnosis the production line for radiating the surgery tools. Its obtained results are compared with the two traditional fuzzy–neural networks diagnostic systems [10]. Tables (1, 2 &3) and figures (4, 5) are represented these comparisons.

From this comparison, it is found that, the proposed system can speed-up the diagnostic process and decrease its time. It can diagnose more complex faulty systems easily, quickly and achieve higher accuracy and reliability. Thus, for example the error of diagnosis the power supply by the fuzzy-neural network diagnostic system is 2.1766e-004 in 4.14 min. While, the neural network diagnostic system is 2.4724e-004 in 5.52 min. On the other hand, the proposed system can significantly decrease the error of the system to 1.4736e-004 and also decrease the time to 2.32 min. However, the proposed system can improve the performance of the neural networks and the fuzzy-neural networks diagnostic systems.

Table (1): Results of the Proposed Diagnostic System

Output from Proposed Fuzzy-Neural Network Diagnostic System	Fault Type	Error	Time
0.9687 0.0145 0.0100 0.0000 0.0003 0.0002	Power supply (y1)	1.4736e-004	2.32 min
0.0061 0.9558 0.0000 0.0083 0.0035 0.0004	Engine speed sensor (y2)	1.5221e-004	2.17 min
0.0124 0.0000 0.9779 0.0000 0.0065 0.0091	Clutch engaging sensor (y3)	1.4324e-004	2.53 min
0.0000 0.0061 0.0000 0.9853 0.0041 0.0062	Choosing motor (y4)	1.6235e-004	2.48 min
0.0043 0.0028 0.0042 0.0064 0.9819 0.0043	Speed sensor (y5)	1.4152e-004	3.12 min
0.0000 0.0002 0.0064 0.0081 0.0011 0.9863	Input axis speed signal (y6)	1.6373e-004	2.78 min

Table (2): Results of the Traditional Fuzzy Neural Network Diagnostic System

Output from Traditional Fuzzy-Neural Network Diagnostic System	Fault Type	Error	Time (min.)
0.9633 0.0143 0.0102 0.0000 0.0032 0.0001	Power supply (y1)	2.1766e-004	4.14
0.0050 0.9456 0.0000 0.0047 0.0065 0.0003	Engine speed sensor (y2)	2.5221e-004	4.27
0.0124 0.0000 0.9779 0.0000 0.0065 0.0091	Clutch engaging sensor (y3)	2.4324e-004	4.57
0.0135 0.0021 0.7862 0.0013 0.0031 0.0052	Choosing motor (y4)	2.7255e-004	4.82
0.0012 0.0038 0.8542 0.0047 0.7814 0.0039	Speed sensor (y5)	2.6452e-004	4.93
0.0022 0.0001 0.0164 0.0037 0.0028 0.8893	Input axis speed signal (y6)	2.8323e-004	5.18

Table (3): Traditional Neural Network Diagnostic System

Output from Neural Network Diagnostic System	Fault Type	Error	Time
0.9687 0.0145 0.0100 0.0000 0.0003 0.0002	Power supply (y1)	2.4724e-004	5.52 min.
0.0025 0.9828 0.0000 0.0034 0.0079 0.0000	Engine speed sensor (y2)	2.7523e-004	5.31 min
0.0294 0.0000 0.9632 0.0003 0.0023 0.0118	Clutch engaging sensor (y3)	2.8744e-004	5.64 min
0.0000 0.0024 0.0000 0.9786 0.0155 0.0081	Choosing motor (y4)	2.9256e-004	5.73 min
0.0006 0.0119 0.0027 0.0109 0.9584 0.0028	Speed sensor (y5)	3.2542e-004	5.82 min
0.0011 0.0000 0.0131 0.0164 0.0037 0.9825	Input axis speed signal (y6)	3.3413e-004	6.18 min

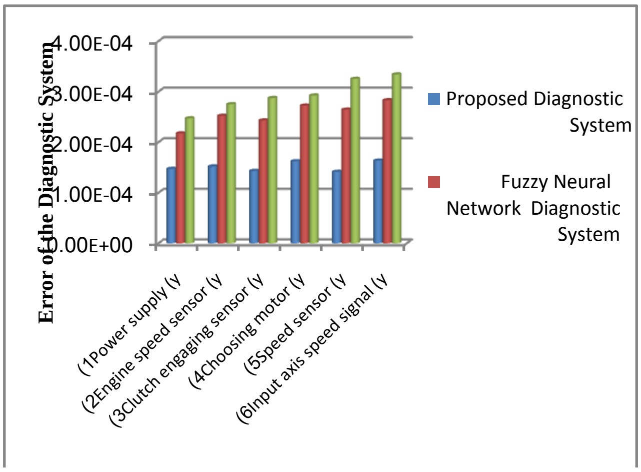

Fig. (4): A comparison of the Error for the Different Diagnostic Systems.

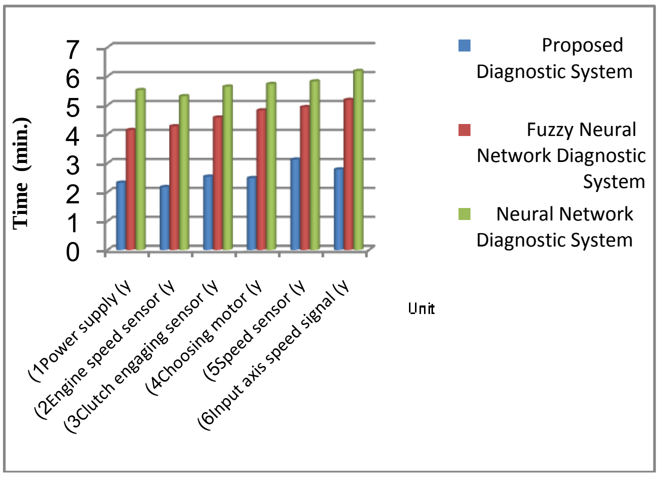

Fig. (5): A comparison of the Time of the Different Diagnostic Systems.

5. CONCLUSIONS

Increasing the complexity of the modern systems based on the new efficient technologies, increasing the needs for automatic diagnostic systems have the ability to deal with these modern technologies.

The proposed system introduces a fault diagnostic system that integrates the fuzzy logic and neural network to diagnose the faults of the complex devices. It can combine the advantages of fuzzy fault diagnosis with those of the neural network. Fuzzy logic control can deal with the faults that cannot determine with deterministic values and can generate the rules for the diagnosis easily and quickly. On the other side, the neural network can diagnose the faults successfully but it suffers from the delay in achieving the required diagnosis. However, the proposed system can have the advantages of the fuzzy logic and the neural network in one system and decompose the neural network to deal with the complex devices.

The proposed system is applied for the production line for radiating the surgery tools as a case of study for a practical system. The obtained results from the proposed system are compared with two other fault diagnostic systems. The proposed system has proved its significant improvement for the performance of the diagnostic systems. Thus, it has increased the accuracy of the diagnosis; scaled-up the size of its diagnostic devices, decreased the time for the diagnostic process.

6. REFERENCES

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