Critical Review on Application of Artificial Neural Networks in The Mechanical Engineering

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Abstract- *Artificial neural network may probably be the single most successful technology in the last two decades which has been widely used in a large variety of applications in various areas. An artificial neural network, often called a neural network, is a mathematical model that is inspired by the structure and function of biological neural networks in the brain. An artificial neural network is a powerful, versatile tool. Artificial neural networks have been successfully used in various applications such as biological, medical, industrial, control engineering, software engineering, environmental, economical, and social applications.*

Keywords- Artificial Neural Networks, Industrial Engineering, Control Engineering, software Engineering

I. INTRODUCTION

Artificial intelligence is an emerging technology science that studies and develops the theory, technology and application systems for simulating and extending human intelligence, involving disciplines such as psychology, cognitive science, thinking science, information science, systems science and bioscience. The Artificial intelligence is in fact the simulation of the process of data interaction of human thinking, hoping to understand the essence of human intelligence and then produce a smart machine, this intelligent machine can be the same as human thinking to respond and deal with the problem [1].

With the continuous progress of science and technology, mechanical engineering is also constantly evolving and changing, from the traditional mechanical Engineering to the electronic and mechanical engineering. And its level of automation and intellectualization has a continuous improvement, it went into a new stage of development, thus, the combination of artificial intelligence technology and mechanical and electronic Engineering has become a hotspot.

Artificial intelligence technology is applied under the premise of the development of computer technology, which improved the computer technology through the analysis of it to achieve the realization of intelligent technology. When intelligent technology being applied in mechanical and electrical engineering, it mainly achieved the automation control of mechanical engineering, the applications of artificial intelligence in mechanical and electrical engineering is not only the use of, computer technology, but also combined with information technology, psychology, linguistics and other knowledge [2].

The purpose of this paper is to report the composition and development of artificial intelligence, as, well as the relationship between artificial intelligence and mechanical and electronic engineering. Most importantly, it aims to study how artificial intelligence is applied in the field of mechanical and electrical engineering.

II. THE RESEARCH DIRECTION OF ARTIFICIAL INTELLIGENCE

2.1 Machine Learning

Machine Learning (ML), which mainly focuses on how the computer simulates human learning behaviour, reorganizes the existing knowledge structure with the knowledge and skills learned, and continuously improve its performance. Machine learning is the core of artificial intelligence and it is the only way for computers to have its own intelligence. At present, the machine learning is used in all areas of artificial intelligence, but cannot be used for deductive reasoning [3].

2.2 Expert System

Expert system (ES) is another important branch of artificial intelligence research [4]. It will explore the general way of thinking into the use of specialized knowledge to solve specific problems.ES will make the theoretical research of the artificial intelligence into practical application; expert system can be seen as a kind of specialized knowledge of computer intelligent program system, it can use expertise and experience provided by experts in specific areas and the use of reasoning techniques in artificial intelligence to solve and simulate complex problems that can often be solved by experts. A basic expert system consists of knowledge base, database, reasoning machine, interpretation mechanism, knowledge acquisition and user interface, as shown in Fig.-1.

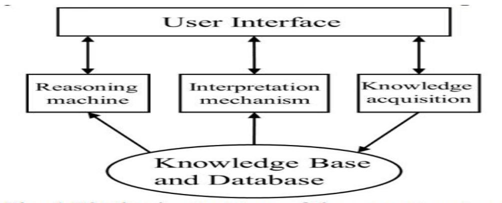

Fig. 1 The basic structure of the expert system

2.3 Pattern Recognition

Pattern recognition research mainly includes two aspects: one is the method of perception of the object, which belongs to the understanding of scientific category; the other one is to achieve pattern recognition with the computer under the condition of the task of the case is determined. The former is the research content of physiologists, psychologists, biologists and neurophysiologists. The latter has been systematically researched by the efforts of mathematicians, informatics experts and computer science workers, and has been applied in text recognition, voice recognition, fingerprint identification, remote sensing and medical diagnosis, etc., it has greatly facilitated the people's lives.

2.4 Neural Network

Artificial Neural Network (ANN) is an arithmetic model obtained by abstracting the human neural network from the perspective of information processing. It is composed of a large number of neurons connected with each other. Each neuron represents a specific output function, called an excitation function. The connection between each of the two neurons represents a weighting through the connected signal, called the weight. When the neural network connection mode, weight and incentive function changes, the network output also will change [5].

2.5. Deep Learning

The concept of deep learning comes from artificial neural network research, belonging to a new field of machine learning [6]. Depth learning refers to artificial intelligence beginning to learn, train it, self-master concepts, and recognize sounds, images and other data from untagged data. This approach is closer to the human brain. Deep learning is mainly to build a deep structure to learn multi-level representation, not specifically refers to a machine learning algorithm or model, but a technology.

III. THE CONCEPT OF MECHANICAL AND ELECTRONIC ENGINEERING

Mechanical and electrical engineering is a science and technology covering all kinds of science, the core of which is mechanical electronics, combined with related knowledge of information technology and intelligent network. The theory of these disciplines has been widely used in mechanical and electrical engineering. In the design of mechanical and electrical engineering, it is necessary to integrate the computer technology, network technology and mechanical-related technology, combining the different mechanical components to improve the design. Although the knowledge is very complex in the design of the mechanical and electronic engineering, the design is relatively simple, the structure is not complicated, and has good performance. Mechanical and electronic engineering has high efficiency, small size when it went to production, which replaced the traditional machinery [7].

IV. THE RELATIONSHIP BETWEEN ARTIFICIAL INTELLIGENCE AND MECHANICAL AND ELECTRONIC ENGINEERING

At present, artificial intelligence technology is often used in the diagnosis of mechanical engineering failure [8-10]. In general, artificial intelligence-based fault diagnosis techniques include rule-based reasoning (RBR), case-based reasoning (CBR), and fault-based tree fault diagnosis. Based on the basic composition and basic principle of the traditional expert system, a mechanical fault diagnosis expert system based on RBR and CBR reasoning is constructed.

The overall structure is shown in Fig- 2. The system includes maneuver case database, fault diagnosis rule database, fault diagnosis database, fault reasoning machine, knowledge processing, fault diagnosis process interpreter, learning system and expert system man-machine interface.

The basic working process of the diagnosis system is: Firstly, the user input the online data monitored by the machine through the man-machine interface. Secondly, reasoning machine activate the corresponding rules to obtain diagnostic results according to the positive reasoning mechanism, it will provide diagnostic expert advice, and then retrieve the case in the database through a certain algorithm, subsequently, get the most similar case, calculate the similarity according to the historical case, and complete the mechanical fault diagnosis with high efficiency. Finally, it will further improve the expert diagnosis system by adding new cases.

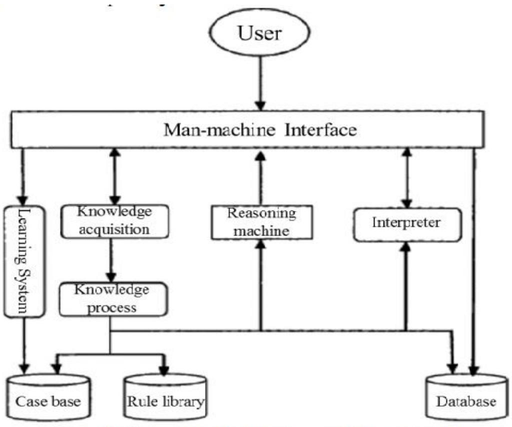

Fig. 2 The overall structure of the system

V. APPLICATION OF ANN

5.1 Intelligent Diagnostic System for Rotating Machinery

From the situation of fault diagnosis of mechanical equipment, during the development of several years, the theory and method of fault diagnosis technology of rotating machinery has been improved day by day. In the practical application, it has achieved great economic benefits. In this paper, the fan diagnosis system is used as an example; in fact, it is the universal integrated neural network diagnosis system in the fan fault diagnosis application.

The system is composed of two parts: fan and motor. According to the type of monitoring parameters, the main system can be divided into five subsystems: vibration, temperature, noise, oil and performance, in which the fault diagnosis and decision system is core of the whole intelligent system.

5.2 Intelligent Diagnosis System for Reciprocating Machinery

Because the reciprocating machinery has a set of high-speed reciprocating motion quality, its kinematics and dynamic morphology is much more complex than the rotating machinery, fault diagnosis is more difficult. The research about failure mechanism and diagnostic methods of research is not enough. Diesel engine is a typical reciprocating machine; integrated neural network diagnos is system is actually a universal integrated neural network diagnostic system in the applications of diesel engine fault diagnosis.

Diesel engine failure can be divided into performance failure and mechanical failure. The diagnosis of performance faults can be achieved using a sub-neural network, with performance parameters as input, such as power, speed, cylinder pressure, water temperature and soon. The mechanical fault is diagnosed by two sub neural networks, and the integrated neural network diagnosis system is formed by using the commonly used vibro acoustic (VA) signal and oil analysis information as input.

5.3. Applications of ANN in Material Science and Industry

5.3.1. Artificial Neural Networks for Material Identification, Mineralogy and Analytical Geochemistry Based on Laser-Induced Breakdown Spectroscopy

Artificial Neural Networks (ANN) are used nowadays in a broad range of areas such as pattern recognition, finances, data mining, battle scene analysis, process control, robotics, etc. Application of ANN in the field of spectroscopy has generated a long-standing interest of scientists, engineers and application specialists. The ANN' capability of producing fast, reliable and accurate spectral data processing has become, in many cases, a bridging mechanism between science and application. A particular example of how ANN can transform plasma emission spectroscopy that is quit challenging to model, into a turnkey ready to use device.

Laser-Induced Breakdown Spectroscopy (LIBS) is a material-composition analytical technique gaining increased interest last decade in various application fields, such as geology, metallurgy, pharmaceutical, bio-medical, environmental, industrial process control and others (Cremer & Radziemski, 2006; Miziolek et al., 2006). It is in essence a spectroscopic analysis of light emitted by the hot plasma created on a sample by the laser-induced breakdown. LIBS offers numerous advantages as compared to the standard elemental analysis techniques (X-ray fluorescence or X-ray diffraction spectroscopy, inductively coupled plasma spectroscopy, etc.), such as: capability of remote analysis in the field, compact instrumentation, detection of all elements and high spatial resolution. Such features as minimum or no sample preparation requirement and dust mitigation using "cleaning" laser shots are especially important for field geology and remotely operated rover-based instruments.

Classification & identification techniques are also used in conjunction with LIBS to define material identity and even composition. In relatively simple cases classification and identification of samples can be achieved by evaluating the line ratios or the patterns of a LIBS spectrum (Monch et al., 1997; Samek et al., 2001; Sattmann et al., 1998). More sophisticated classification methods such as, principle components analysis (PCA), soft independent modeling of class analogy (SIMCA) and partial least-squares discriminate analysis (PLS-DA), have been studied and produced very promising results (Sirven et al.,2007; Clegg et al., 2009). However, the above techniques being based on linear processing have difficulty to take into account nonlinear effects.

5.3.2 Application of Artificial Neural Networks in the Estimation of Mechanical Properties of Materials

In today's industry, it is imperative that a thorough knowledge of the mechanical properties of materials be known to the designer in order to come up with a design of parts, tools, or instruments that will meet the highly competitive industrial requirements. It is well known that mechanical properties of various materials are in turn highly affected by the manner in which they are subjected to loadings of both static and fatigue types, and by its manufacturing process, in particular the heat treatment the material receives during its manufacturing. This further makes it required to perform the proper experiments and laboratory tests with regard to fatigue in the field of fatigue mechanics in order to obtain the necessary knowledge for the material properties for design purposes. It is emphasized that such properties obtained from monotonic tests are of no value and by no means recommended.

Metallurgical engineers often attempt to obtain their desired material properties and efficiencies by making variations in the parameters governing the manufacturing process. On the other hand, yet, the high costs of fatigue tests as compared with those of the simple monotonic tests, as well as the need for complex testing equipment are the major drawbacks in the way of such tests, encouraging the use of approximate and empirical mathematical models based on the data obtained from the monotonic tests. This has been quite evident among researchers and industry alike, as indeed indicated by the variety of ongoing articles published in the field. In the area of materials engineering as well, the knowledge of the effect of different manufacturing processing parameters on the material properties in view of the highly expensive nature of the tests are also of particular interest. Use of Artificial Neural Network (ANN) models is considered as a less expensive, less tedious, more efficient, and highly reliable alternative means for the estimation of the material fatigue properties using the data obtained from the monotonic tests. In addition, the ANN methodology was also employed for the parameter estimation related to the manufacturing process of materials. The method was also used to investigate and infer the manner in which such material properties are affected by variations in the parameters that are the main governing elements of these properties.

L.A.Dobrzanski etc, study the results of the research connected with the development of new approach based on the neural network to predict chemical composition and cooling rate for the mechanical properties of the Mg-Al-Zn cast alloys. The independent variables on the model are chemical composition of Mg-Al-Zn cast alloys and cooling rate. The dependent parameters are hardness, ultimate compressive strength and grain size.

NS Balaji etc,did the research on tensile, flexural, and impact behaviors of zeafiber-reinforced polyester composites were evaluated. The different proportion of fiber length, fiber content in weight percentage, and molding pressure was used as process parameters in the fabrication of zea–polyester composites. The parameters and their levels were selected based on full factorial design as per the design of experiments. The composites were fabricated and tested as per ASTM standards. An artificial neural network algorithm was developed to predict the mechanical behaviors over the specified range of conditions, and the average absolute percentage of error of less than 4% was observed for tensile, flexural, and impact models.

5.3.3. Optimum Design and Application of Nano-Micro-Composite Ceramic Tool and Die Materials with Improved Back Propagation Neural Network

The computational intelligence (CI) technique, as an offshoot of artificial intelligence (AI), is a kind of heuristic algorithm including three categories: neural network, fuzzy system and evolutionary computation. Genetic algorithm (GA) and artificial neural network (ANN) are the two important computational intelligence techniques. In recent, the two techniques especially the ANN have got successful application in the material design of ceramics and metal matrix composites, etc. For instance, some researchers used ANN to predict the functional properties of ceramic materials from compositions (Scott et al, 2007) or the bending strength and hardness of particulate reinforced Al-Si-Mg aluminum matrix composites (Altinkok & Korker, 2004) or the mechanical properties of ceramic tool (Huang et al, 2002) or the percentage of alumina in Al2O3/SiC ceramic cakes and the pore volume fraction (Altinkok & Korker, 2005), etc.

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ANN is a kind of self-learning technology and back propagation(BP) neural network is one of the simply and commonly used network architectures. BP is based on the gradient descent method where connection weights and thresholds are modified in a direction corresponding to the negative gradient of a backward-propagated error measure (Jiang &Adeli, 2004). Although BP neural network has an advantage of high accuracy, it is often plagued by the local minimum point, low convergence or oscillation effects. In order to overcome the disadvantage of BP neural network, GA is usually used to improve the BP neural network. GA has a strong searching capability and high Probability in finding the global optimum solution which is suitable for the early stage of data searching. Although these two techniques seem quite different in the number of involved individuals and the process scheme, they can provide more power of problem solving than either alone (Yen &Lu, 2002; Yao, 1999; Gen & Cheng, 2000). Therefore, many researchers have attempted to use GA to improve BP neural network in order to achieve the complementary advantages (Sexton, 1998; Gupta & Sexton, 1999).

5.4. Application of Bayesian Neural Networks to Predict Strength and Grain Size of Hot Strip Low Carbon Steels

Mohammad reza etc, study on the effects of chemical composition and process variables on the tensile strength of hot strip mill products were modeled by Artificial Neural Network (ANN) moreover a Bayesian ANN model assisted by RJMCMC is capable of predicting the grain size of hot strip low carbon steels and can be used as a function of steel composition.

The relative importance of each input variable was evaluated by sensitivity analysis for tensile strength. The influence of chemical composition on final tensile strength is much more pronounced than process parameters. Furthermore, grain size model recognizes the effects of relevant elements in grain refining. These are manganese, silicon and vanadium. Silicon concentration shows determining role this effect have not reported in the literature and vanadium reveals great impact on grain refining phenomena.

The results show the effects of the parameters are too complex to model with a simple linear regression technique. The developed ANN models can be used as guide to control the final mechanical properties of commercial carbon steel products.

The major advantage of these methods is selection of useful inputs in complex problems with many inputs. Because many problems in materials science and engineering are similar, this method is useful for solving them.

5.5. Artificial Neural Network Prosperities in Textile Applications

Textile industry, deal with numerous large inputs and possible outputs parameters and always feed with a complex interdependence between parameters, it is highly unlikely that an exact mathematical model will ever be developed.

Furthermore, since there are many dependent and independent variables during different textile progress, it becomes difficult to conduct and to cover the entire range of the parameters. Moreover, the known and unknown variables cannot be interpolated and extrapolated in a reasonable way based on experimental observations or mill measurements due to the shortage of knowledge on the evaluation of the interaction and significance at weight contributing from each variable. ANN uses in Textile Industry for following data prediction these are fiber classification ;Yarn,fabric,nonwoven and cloth defect and categorization; Yarn defect; Woven fabric defects;Knited fabric defects: Nonwoven defects; cloth defects; Yarn and fabric properties prediction and modeling; Mechanical behavior prediction of textiles.

5.6. The applications of Artificial Neural Networks to Engines

The automotive sector has applied neural networks models in several different cases. Their main implementation is seen in control design in the area of engine operation. Hence, in engine development neural networks are used for control problems such as fuel injection, output performance or speed (Hafner et al., 2000; Ouladsine et al., 2004). In addition, advanced control strategies as variable turbine geometry (VGT), exhaust gas recirculation(EGR) or variable valve timing (VVT) have been in the focus of ANN modeling (Thompsonet al., 2000). Nevertheless, the application is also used for virtual sensing such as emissions (Hanzevack, 1997; Atkinson, 2002) or as described in Prokhorov (Prokhorov, 2005) for misfire detection, torques monitoring or tyre pressure change detection. The combustion process itself has been investigated and parameters been modeled with neural networks by different authors (Potenza et al., 2007; He et al., 2004). Potenza et al. developed a model estimating Air-to-Fuel Ratio (AFR) or in-cylinder pressure and temperature on the basis of crankshaft kinematics and its vibrations. In the work of He et al.combustion parameters and emissions are modeled under the consideration of boost pressure and EGR.

5.7. A Comparison of Speed-Feed Fuzzy Intelligent System and ANN for Mach inability Data Selection of CNC Machines

The conventional method for selecting machining parameters such as cutting speed and feed rate is based on data from machining hand books and/or on the experience and knowledge of the operator or CNC programmer. The parameters chosen in most cases are extremely conservative to protect over- matching errors from tool failures such as deflection, wear, breakage, etc. Accordingly, the metal removal rate is low due to the use of such conservative machining parameters (Park & Kim, 1998).Guidelines on machinability data selection is normally made on the basis of the manufacturer's machinability hand book (Hashmi et al., 2003). Using machining data handbook for the choice of cutting conditions for material hardness that lies in the middle of a group is simple and straight forward. But there exists a degree of vagueness in boundary cases, where two choices of cutting speeds are applicable for one choice of material hardness. In this situation, the skilled operator makes a decision on the appropriate cutting speed, based on his experience. However, this method of data selection by individual operators is not very desirable, because it may vary from operator to operator. Therefore, it is desirable to have an operator independent data selection system for choosing machining operation (Hashmi et al., 1998).

While the output variables of the machining process depend on the cutting conditions, the decision concerning the selection of the cutting parameters have an important influence on the extent, cost and quality of the production. Due to the increased use of CNC machines and severe competition between the makers, the importance of precise optimization cutting conditions has increased (Cus & Zuperl, 2006).

Fuzzy logic can be applied to any process in which a human being plays an important role which depends on his subjective assessment (EL Baradie, 1997).For the selection of machining parameters different methods have been proposed. Hashmiet al. (1998, 1999) applied fuzzy logic with triangular shape for selecting cutting conditions in machining operations using single input (material hardness) and single output (cutting speed) model. El Baradie (1997) presented the development of a fuzzy logic model for machining data selection using material hardness (input) and cutting speed (output) with triangular shape. A study was made by Wong et al (1999) to obtain a generalized model for metal cutting data selection. Wong and Hamouda (2003) developed an online knowledge based expert system for machinability data selection using two input-one output model for cutting speed and one input-one output model for feed rate.

Cus and Zuperl (2006) proposed a neural network approach for the optimization of cutting conditions. Neural networks were used by Wong and Hamouda (2003b) in the representation of machinability data to predict optimum machining parameters. Zuperl and Cus (2003) proposed a neural based approach to optimization of cutting parameters to represent the manufacturer's preference structure.

Lee and Tarng (2000) used a polynomial network to construct the relationship between the machining parameters and cutting performance. An optimization algorithm of sequential quadratic programming method was used to solve the optimal machining parameters.

A gradient based multi criteria decision making approach was applied by Malakooti and Deviprasad (1989) to aid the decision-maker in setting up machining parameters in metal cutting. The optimal machining parameters for continuous profile machining for turning cylindrical stock were determined by Saravanan et al. (2003) using simulated annealing and genetic algorithm. Vitanov et al. (1995) introduced a knowledge-based interactive approach for optimum machining parameter selection in metal cutting using multi-objective probabilistic geometric programming and artificial techniques. The machining parameters were optimized based on the Taguchi method in a proposed model by Nian et al. (1999) considering the multiple performance characteristics including tool life, cutting force and surface finish.

5.8. Control and Robotic Engineering Artificial Neural Network–Possible Approach to Nonlinear System

Artificial Neural Network is nowadays a popular methodology with lots of practical and industrial applications. As introduction, some concrete examples of successful application of ANN can be mentioned, *e.g.* mathematical modeling of bioprocesses [Montague et al.,1994], [Teixeira et al., 2005], prediction models and control of boilers, furnaces and turbines [Lichota et al., 2010] or industrial ANN control of calcinations processes, or iron ore process [Dwarapudi, et al., 2007].

5.8.1. Neural Networks' Based Inverse Kinematics Solution for Serial Robot Manipulators Passing Through Singularities

Before moving a robot arm, it is of considerable interest to know whether there are any obstacles present in its path. Computer-based robots are usually served in the joint space, whereas objects to be manipulated are usually expressed in the Cartesian space because it is easier to visualize the correct end-effectors position in Cartesian coordinates than in joint coordinates. In order to control the position of the end-effectors of the robot, an *inverse kinematics (IK)* solution routine should be called upon to make the necessary conversion (Fuet al., 1987).

Solving the inverse kinematics problem for serial robot manipulators is a difficult task; the complexity in the solution arises from the nonlinear equations (trigonometric equations)occurring during transformation between joint and Cartesian spaces. The common approachfor solving the IK problem is to obtain an analytical close-form solution to the inverse transformation, unfortunately, close-form solution can only be found for robots of simple kinematics structure. For robots whose kinematics structures are not solvable in close-form; several numerical techniques have been proposed; however, there still remains several problems in those techniques such as incorrect initial estimation, convergence to the correct solution cannot be guaranteed, multiple solutions may exist and no solution could be found if the Jacobian matrix was in singular configuration (Kuroe et al., 1994; Bingual et al., 2005).
A velocity singular configuration is a configuration in which a robot manipulator has lost at least one motion degree of freedom DOF. In such configuration, the inverse Jacobian will not exist, and the joint velocities of the manipulator will become unacceptably large that often exceed the physical limits of the joint actuators. Therefore, to analyze the singular conditions of a manipulator and develop effective algorithm to resolve the inverse kinematics problem in the singular configurations is of great importance (Hu et al., 2002).

Many research efforts have been devoted towards solving this problem, one of the first algorithms employed was the Resolved Motion Rate-Control method (Whitney, 1969), which uses the pseudo inverse of the Jacobian matrix to obtain the joint velocities corresponding to a given end-effector velocity, an important drawback of this method was the singularity problem. To overcome the problem of kinematics singularities, the use of a damped least squares inverse of the Jacobian matrix has been later proposed in lieu of the pseudo inverse (Nakamura & Hanafusa, 1986; Wampler, 1986).Since in the above algorithmic methods the joint angles are obtained by numericalintegration of the joint velocities, these and other related techniques suffer from errors dueto both long-term numerical integration drift and incorrect initial joint angles. To alleviatethe difficulty, algorithms based on the feedback error correction are introduced (Wampler &Leifer, 1988). However, it is assumed that the exact model of manipulator Jacobian matrix of the mapping from joint coordinate to Cartesian coordinate is exactly known. It is also notsure to what extent the uncertainty could be allowed. Therefore, Most Research On robot control has assumed that the exact kinematics and Jacobian matrix of the manipulator from joint space to Cartesian space are known. This assumption leads to several open problems in the development of robot control laws (Antonelli et al., 2003).Intelligent control has been introduced as a new direction making control systems able to attribute more intelligence and high degree of autonomy. Artificial Neural Networks (ANN) have been widely used for their extreme flexibility due to the learning ability and the capability of non linear function approximation, a number of realistic control approaches have been proposed and justified for applications to robotic systems (D'Souza et al.,2001; Ogawa et al., 2005; Köker, 2005; Hasan et al., 2007; Al-Assadi et al., 2007), this fact leads to expect ANN to be an excellent tool for solving the IK problem for serial manipulators overcoming the problems arising.Studying the IK of a serial manipulator by using ANNs has two problems, one of these is the selection of the appropriate type of network and the other is the generating of suitable training data set (Funahashi, 1998;Hasan et al., 2007). Different methods for gathering training data have been used by many researchers, while some of them have used the kinematics equations (Karilk & Aydin, 2000; Bingual et al.,2005), others have used the network inversion method (Kuroeetal.,1994;Köker,2005),another have used the cubic trajectory planning (Köker et al., 2004) and others have used a simulation program for this purpose (Driscoll, 2000). However, there are always kinematics uncertainties presence in the real world such as ill-defined linkage parameters, links flexibility and backlashes in gear train.
A learning method of a neural network has been proposed by(Kuroe et al., 1994), such that the network represents the relations of both the positions and velocities from the coordinate to the joint space coordinate. They've driven a learning algorithm for arbitrary connected recurrent networks by introducing adjoin neural networks for the original neural (Network inversion method). On-line training has been performed fora2DOFrobot.(Graca and Gu,

1993) have developed a Fuzzy Learning Control algorithm. Based on the robotic differential motion procedure, the Jacobian inverse has treated as a fuzzy matrix and has learned through the fuzzy regression process. It was significant that the fuzzy learning control algorithm neither requires an exact kinematics model of a robotic manipulator, nor a fuzzy inference engine as is typically done in conventional fuzzy control. Despite the fact that unlike most learning control algorithms, multiple trials are not necessary for the robot to “learn” the desired trajectory. A major drawback was that it only remembers the most recent data points introduced; the researchers have recommended neural networks so that it would remember the trajectories as it traversed them.

VI. CONCLUSION

In the field of mechanical engineering, there have been many researchers on the basis of neuralnetwork theory, method, technique and its application has done a lot of pioneering or exploratory work, a lot of achievements. But, look from domestic actual situation, theory, method and technology of artificial neural network in the application and development in the field ofmechanical engineering, is still in the preliminary stage. Artificial neural networks have been successfully used in various applications such as biological, medical, industrial, control engineering, software engineering, environmental, economical, and social applications. At present, there are two opposite views: one is that the artificial neural network has been research for many years, no more advanced and novel, this is a kind of stagnation and inaction; The other opposite, always think of artificial neural network is a theoretical research work, not for actual production. For these two views, in particular the right decisions at this stage, comprehensive planning and positive guidance, upgrading of machinery products, machinery industry for the future to contribute to the revitalization and take-off of, also can make the artificial neural network in the field of mechanical engineering with new opportunities and greater development.

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