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ARTIFICIAL INTELLIGENCE TECHNIQUES FOR MACHINING PERFORMANCE: A REVIEW

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ABSTRACT

This paper reviews the approaches of artificial neural network (ANN) on machining performance. ANN considered as a successful approach to modelling the machining process for predicting performance measures through the development of an expert system. An expert system is an interactive intelligence program with an expert-like performance in solving a particular type of problem using knowledge base, inference engine and user interface. The approaches of ANN in past years with respect to cutting forces, surface roughness of the machined work piece, tool wear and material removal rate were reviewed. Results from literatures indicated that the ANN has the ability in generalizing the system characteristics by predicting values close to the actual measured ones.

Keywords: artificial neural network, cutting force, surface roughness, tool wear, material removal rate.

INTRODUCTION

The success of automated manufacturing relies to a large extent on the development of computer-based learning schemes that are able to code operational knowledge. Machining processes are usually too complicated to warrant appropriate analytical models and most of the time, analytical models are developed based on many simplified assumptions, which contradict reality. More importantly, it is sometimes difficult to adjust the parameters of the abovementioned models according to the actual situation of the machining process. Therefore, artificial neural networks, (ANN) can map the input/output relationships and possess massive parallel computing capability, have attracted much attention in research on machining processes. ANN provides significant advantages in solving processing problems that require real-time encoding and interpretation of relationships among variables of high-dimensional space. ANN has been extensively applied in modeling many metal-cutting operations such as turning, milling and drilling. The general ability of the network is actually dependent on three factors. These factors are the selection of the appropriate input/output parameters of the system, the distribution of the dataset, and the format of the presentation of the dataset to the network. The selection of the neuron number, hidden layers, activation function and training algorithm are very important to obtain the best results. Rangwala and Dornfeld (1990), presented a scheme that used a multilayered perceptron neural network to model the turning process and an augmented Lagrange multiplier method to optimize the material removal rate. The prediction of surface roughness in computer numerically controlled (CNC) face milling was studied Benardos and Vosniakos, (2002). The authors were trained an artificial neural network (ANN) with the Levenberg–Merquardt algorithm and determined the influence of the factors using Taquchi design of the experimental method. Scheffer et al. (2003) developed an online tool wear monitoring system for hard turning by using a similar approach proposed by Ghasempoor et al. (1999). They combined the static and dynamic neural networks as a modular approach. The static neural networks are used to model flank and crater wear and trained off-line. The dynamic model is trained on-line to estimate the wear values by minimizing the difference between on-line measurements and the output of the static networks that enables the prediction of wear development on-line. This review reports on the approaches of artificial neural network with respect on the surface roughness, tool wear, cutting forces and material removal rate produced during machining.

STRUCTURE OF ARTIFICIAL NEURAL NETWORK

ANN can generally be defined as a structure composed of a number of interconnected units, Kartalopoulos (1996) .Each unit has an input/output (I/O) characteristic and implements a local computation or function. The output of each unit is determined by its I/O characteristic, its interconnection to other units and (possibly) external inputs, and its internal function. The network usually develops an overall functionality through one or more forms of training. The fundamental unit or building block of the ANN is called artificial neuron (called neuron from here on), Skapura (1996). The neuron has a set of inputs (X_i) weighted before reaching the main body of the processing element. In addition, it has a bias term, a threshold value that has to be reached or exceeded for the neuron to produce a signal, a non-linearity function (f_i) that acts on the produced signal (R_i), and an output (O_i). The basic model of a neuron is illustrated in Figure 1.

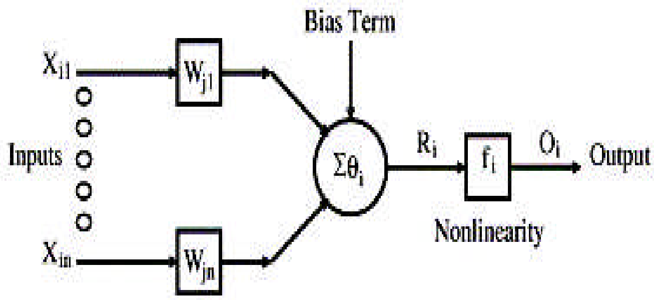

Figure 1: Basic model of artificial neuron.

Neural networks are developed to model the way in which the human brain performs a particular task, or processes information. A neural network is a massively parallel distributed processor that has a neural propensity for storing experiential knowledge and making it available for use. The central motivation underlying thedevelopment of artificial neural systems is to provide a new type of computer architecture in which knowledge is acquired and stored over time through the use of adaptive learning algorithms. Some of its advantages are adoption and learning, ease of implementation, and self organization. A neural network is defined mainly by three features: topology, functionality and learning. Topology refers to the number of nodes in each layer, and the way nodes are connected. Functionality refers to the transfer function and discriminatory function (if any) of each node, and the cost function of the network outputs. Learning refers to the learning algorithm and the values of the learning parameters (e.g., learning rates, and momentum rates). According to their topology in operation phase, neural networks can be generally divided into two categories: feedback networks and feed forward networks. Feed forward neural networks are somewhat simple in structure and easily analyzed mathematically. The back-propagation network is the first and most commonly used feed forward neural network because there exists a mathematically strict learning scheme to train the network and guarantee mapping between inputs and outputs.

ARTIFICIAL INTELLIGENCE TECHNIQUES FOR PREDICTION OF MACHINING PERFORMANCE

Surface Roughness

Surface roughness is a measure of the technological quality of a product and a factor that greatly influences manufacturing cost. It describes the geometry of the machined surface and combined with the surface texture, which is process dependent, can play an important role on the operational characteristics of the part (e.g. appearance of excessive friction and/or wear). Surface roughness is a commonly encountered problem in machined surfaces. It is defined as the finer irregularities of surface texture, which results from the inherent action of the production process. Consequently, surface roughness has a great influence on product quality, and the part functional properties such as lubricant retentivity, void volume, load bearing area, and frictional properties. Furthermore a good-quality machined surface significantly improves fatigue strength, corrosion resistance, and creep life (Stark and Moon, 1999). Surface roughness is consisting of a multitude of apparently random peaks and valleys. When two rough surfaces are brought to be in contact, it is occurred in smaller area, which is called the real area of contact. This area is not only a function of the surface topography but also on the study of interfacial phenomena, such as friction and wears (Bhushan, 1999). Lee and Ren (1996) were explained that surface roughness plays an important role in affecting friction, wear, and lubrication of contacting bodies. Lundberg (1995) has investigated the effect of surface roughness on the lubricant film characteristics under conditions of combined normal and sliding motion. At this condition, ANN plays a role to estimate the surface roughness in machining in order to enhance the performance of machining process.

Azouzi and Guillot (1997) were examined the feasibility of neural network based sensor fusion technique to estimate the surface roughness and dimensional deviations during machining. This study concludes that the depth of cut, feed rate, radial and z-axis cutting forces are the required information that should be fed into neural network models to predict the surface roughness successfully. In addition to those parameters, Risbood et al. (2003) added the radial vibrations of the tool holder as additional parameter to predict the surface roughness. They observed that the surface finish first improves with increasing feed but later it starts to deteriorate with further increase of feed. Lee and Chen (2003) were proposed an online surface roughness recognition system using neural networks by monitoring the vibrations caused by the tool and workpiece motions during machining. They obtained good results but their study was limited to regular turning operations of mild steels. Benardos and Vosniakos (2002) were studied the surface roughness in machining and confirmed the effectiveness of neural network approaches. The factors considered in the experiment were the depth of cut, the feed rate per tooth, the cutting speed, the engagement and wear of the cutting tool, the use of cutting fluid and the three components of the cutting force. This paper presents the development of a neural network model using elements from the theory of face milling, the surface roughness formation mechanism and based on design of experiment (DOE) methodology, concerning finish face milling of Al alloy in a vertical axis CNC milling machine. The goal was to train ANN to include the most important factors affecting surface roughness in order to make accurate and consistent predictions for any new combination of values for these factors. The workpiece material used was series 2 Aluminum alloy normally used in aerospace applications. The Levenberg–Marquardt algorithm selected for training the ANN was a variation of the classic backpropagation algorithm that, unlike other variations that use heuristics, relies on numerical optimization techniques to minimize and accelerate the required calculations, resulting in much faster training. ANN had a good ability to predict the surface roughness and the consistency of ANN in its prediction was also obvious. The approaches of ANN continue in Basheer et al. (2008). The objective of this experiment was to understand the process of surface generation in the precision machining of composites, and to provide an appropriate knowledge-base to train the proposed ANN model to predict the surface roughness. The turning experiments were performed on a CNC machine using polycrystalline diamond (PCD). In order to determine the optimal regularization parameters, Bayesian regularization (combination with Levenberg–Marquardt modification were used to train ANN system. The proposed neural network system shown very good prediction accuracy with coefficient of correlation of $R = 0.977$ and mean absolute error of 10.4% was observed between the actual and predicted value.The authors concluded that ANN uses a feed-forward network and involving Bayesian regularization combined with the Levenberg–Marquardt modification give a good prediction in surface roughness estimation. A multi-layer feed forward ANN, trained using error back-propagation training algorithm (EBPTA) was employed for predicting the surface roughness in turning (Paulo et al., 2008). The simulated multi-layer feed forward ANN architecture consists of 3 neurons in the input layer (corresponding to 3 process inputs, feed rate, spindle speed and depth of cut), 2 neurons in the output layer (corresponding to 2 outputs, R_a and R_t). One hidden layer with 16 neurons was employed and R_a and R_t values was predicted using the ANN model and then compared with the measured values. The comparison for the validation data set was performed and the predicted values follow almost the same trend as that of the actual values for both the surface roughness parameters. It was also found that the maximum absolute error was around 28.29% and 8.91% for R_a and R_t respectively. The authors also concluded that an ANN can capture any degree of non-linearity that exists between the process response and input parameters and exhibits good generalization. ANN models can predict the response for any new input process parameters with high accuracy. In addition, the application of perception-type neural networks to tool-state classification during a metal-turning operation has been studied (Dimla and Dimla, 1999). They investigated both single-layer networks and multi-layer networks and found that the multi-layer networks had better performance than the single-layer tool-state classification.

Besides that, Nalbant et al.(2009) were conducted an experimental investigation of the effects of uncoated, PVD- and CVD-coated cemented carbide inserts and cutting parameters on surface roughness in CNC turning and its prediction using artificial neural networks. In the input layer of the ANNs, the coating tools, feed rate and cutting speed values are used while at the output layer the surface roughness values are used and AISI 1030 steel have been used as a material . They were used to train and test multilayered, hierarchically connected and directed networks with varying numbers of the hidden layers using back-propagation scaled conjugate gradient (SCG) and Levenberg–Marquardt (LM) algorithms with the logistic sigmoid transfer function. The experimental values and ANN predictions are compared by statistical error analyzing methods. Based on the statistical error analysis methods, using SCG technique for average surface roughness, the R^2 value for the training data set was 0.99985, while for the testing data it became 0.99983; the *RMS* values were 0.00069 and 0.00265 and the mean error values were 1.13458% and 1.88698%, respectively. Therefore, the average surface roughness value accurately determined by the ANN by using three input parameter (cutting tools, cutting speed and feed rate) the average surface roughness of the steel parts may be predicted without involving any mathematical modeling. The development of an intelligent product quality model for CNC turning using neural network techniques was also reported by Suneel et al. (2002). The ability of ANN to be a good modelling technique for R_a prediction was mentioned by Tsai et al. (1999) where ANN model gave a high accuracy rate (96–99%) for predicting R_a in the end milling cutting operations compared to the result of the Statistical Regression model. Erzurumlu and Oktem (2007) concluded that the ANN model led to slightly more accurate Ra prediction values compared to the conventional model.

In addition of prediction surface roughness, Karayel et al. (2009) studied a neural network approach for the prediction and control of surface roughness in a computer numerically controlled (CNC lathe machine). The parameters used in the experiment were reduced to three cutting parameters which consisted of depth of cutting, cutting speed, and feed rate. A feed forward multi-layered neural network was developed and the network model was trained using the scaled conjugate gradient algorithm (SCGA), which was a type of back-propagation. It can be seen that in most cases, the neural network prediction was very close to the actual value. The average absolute error was 2.29% for predictions using the model constructed with the abductive network and was 10.75% for predictions using regression analysis Lin et al. (2001). The study has revealed that the predictions using ANN have more accurate results. Karayel (2009) also stated ANN can produce an accurate relationship between cutting parameters and surface roughness. Therefore, ANN can be used for modeling surface roughness so that it can be estimated close to real values before the machining stage.

Oktem et al. (2006) developed Artificial Neural Network (ANN) and Genetic Algorithm for prediction of minimum surface roughness in end milling mold parts. Cutting parameters such as cutting speed, feed, axial–radial depth of cut, and machining tolerance were selected as the input of the ANN architecture where output of the structure was surface roughness. A feed forward neural network was developed to model surface roughness by exploiting experimental measurements obtained from these surfaces. ANN model was integrated with efficient GA to solve the optimization problem. From the result, it can be inferred that a good correlation was obtained between ANN predictions and experimental measurements. It can be also realized that the neural network presents a very good performance. Mohd Zain et al. (2010) were carried out the experiment in end milling machining. Feed forward back propagation was selected as the algorithm and all data samples are tested in real machining by using uncoated, TiAIN coated and SNTR coated cutting tools of titanium alloy. With three nodes in the input layer and one node in the output layer, eight networks are developed by using different numbers of nodes in the hidden layer It was found that the 3–1–1 network structure of the SNTR coated cutting tool gave the best ANN model in predicting the surface roughness value. Most of the investigations mentioned above studied the effect of cutting variables such as speed, feed rate and depth of cut on surface roughness by considering one variable at a time (Choudhury and El-Baradie, 1997).

On the other hand, Tsai and Wang (2001a) compared six types of neural network models and a neuro-fuzzy network in predicting surface roughness. Their study revealed that multilayer feed-forward neural network with hyperbolic tangent-sigmoid transfer functions performed better among feed-forward neural network models. Ho et al. (2002) proposed a method using an adaptive neuro-fuzzy inference system to accurately establish the relationship between the features of a surface image. Their system could effectively predict surface roughness using the cutting parameters. Yilmaz et al. (2006) were used a user friendly fuzzy-based system for the selection of electro-discharge machining process parameters. Effects of other important parameters like current, voltage and machining time on SR were not considered. Kamatala et al. (1996) were developing a fuzzy set theory-based system for predicting surface roughness in a finished turning operation. In contrast of turning process, Chen & Kumara (1998) use a hybrid approach of fuzzy set and ANN-based technique for designing a grinding process and its control.

Tool Wear

Monitoring of machining process is a classic and yet unsolved problem in manufacturing engineering. Cutting tool users cannot afford to ignore the constant changes and advancement being made in the field of tool material technology. The tool should be retracted and changed well before it wears out totally, otherwise the part to be machined may not comply with the specified tolerance due to the use of the worn-out tool. This may also result in poor surface finish of the job, leading to increase in overall production cost due to increase in rework and scrap. In order to solve the problem stated, ANN approaches have been practiced by researcher as the optimization in machining process. Kuo (2000) was conducted a research to estimate tool wear characteristics by using ANN and fuzzy neural network. A intelligence system was proposed, which can predict the amount of tool wear on-line and to compare two ANNs, a feed forward network with an error back propagation (EBP) learning algorithm and a counter propagation network (CPN). Due to the slow training speed of the EBP learning algorithm, three fuzzy decision tables developed by Kuo (1995) are employed to dynamically adjust three training parameters (training rate, momentum, and steepness of activation function). The training and testing results indicate that EBPN can provide much better forecasting results than CPN. However, the disadvantage of EBPN was that it requires a longer training time. Since the difference in MSE values between EBPN and CPN was very large, it was not reasonable to select CPN. In addition, three fuzzy models developed by Kuo (1995) significantly decrease the training time. Therefore, in the integration, only the results from EBPN are chosen. In addition, Sanjay et al. (2005) applied a back propagation neural networks for detection of drill wear. Drill size, feed, spindle speed, torque, machining time and thrust force are given as inputs to the ANN and the flank wear as output. The twist drills were made of high-speed steel (HSS) and the work piece material was mild steel bar and the drill depth was maintained as 30 mm.

Hole Number	5	10	15	20	25	30	35	40
Actual (mm)	0.09	0.18	0.3	0.38	0.46	0.55	0.61	0.69
Statist. Anlys.(mm)	0.14	0.24	0.32	0.4	0.48	0.56	0.61	0.67
ANN 6x10x1 (mm)	0.08	0.18	0.26	0.36	0.45	0.54	0.6	0.68

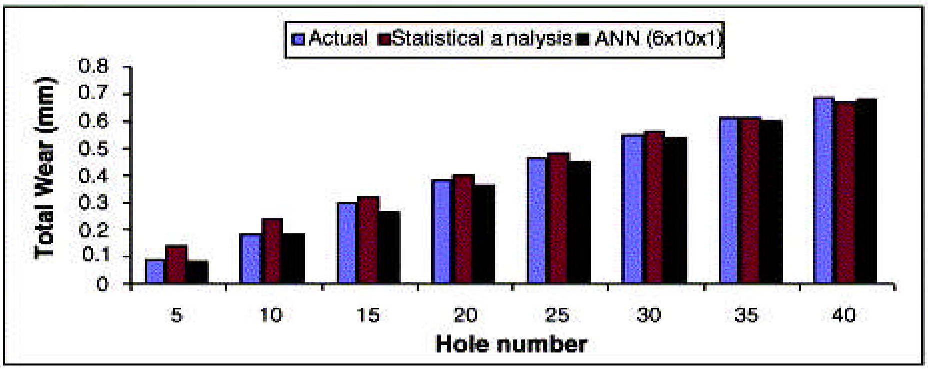

Figure 2: (Tool wear) diameter 8 mm, speed 12.31 m/min and feed 0.19 mm/rev.

Figure 2 shows that this method can be effectively employed in practice as the algorithm was easy and reliable. ANN has shown the capability of generalization and has the ability for its application in tool wear analysis. Panda et al. (2006) also had shown their interest in monitoring drill wear by using a back propagation neural network algorithm. To train the neural network thrust force, torque, chip thickness, spindle speed, feed-rate and drill diameter were used as input parameters and corresponding maximum flank wear has been used as the output parameter. Drilling operations have been performed in mild steel work-piece by high-speed steel (HSS) drill bits over a wide range of cutting conditions. The predicted wear from neural network was very close to the actual wear measured experimentally. Panda et al. (2008) were extended their work with same process but with addition of root mean square (RMS) as input of the structure. It has been also found that the error in prediction of drill wear using neural network model was less than that using the regression model. The power supply line voltage was assumed constant throughout this analysis. However, the line voltage may change over time to time in the shop floor where the machining was carried out. This shows that the simple neural network model can be successfully implemented for online prediction of drill wear using spindle motor current signal.

Noori-Khajavi and Komanduri(1993) were predicted drill wear with the help of a multilayer neural network trained with signals from four sensors namely thrust force, torque and strains in two orthogonal directions to the drill axis. Liu and Anantharaman (1994) used average thrust force, average torque, peak thrust force, peak torque, RMS thrust force, RMS torque, area under the thrust force versus time and the area under torque versus time as the input to the modified back propagation neural network with adaptive activation function slopes for the classification of the drill wear. Lin and Ting (1996) compared different architectures of multilayer feed forward neural network with back propagation training and determined the best architecture for predicting drill wear. Mean values of thrust force and torque signals were used along with the cutting conditions as inputs to the network. Liu et al. (1998) developed a back propagation neural network to predict drill wear state using eight features extracted from the thrust force and torque signals and three cutting conditions (speed, feed, and drill diameter) as input to the network. Abu-Mahfouz (2003) compared several architectures of multilayer neural network with a back propagation training algorithm for drill wear monitoring. Training data set was extracted from the acquired vibration signal from an accelerometer attached to the work piece. It was shown that the frequency domain features such as average harmonic wavelet coefficients, and the maximum entropy spectrum peaks were more efficient in training the network than the time-domain statistical moments.

Singh et al. (2006) developed a multilayer neural network with back propagation training algorithm and tested it for drill wear prediction at different cutting conditions. The network was trained and tested by experimental data containing thrust force, torque, spindle speed, feed-rate, drill diameter and maximum flank wear. Network architecture 5-4-1 with learning rate 0.3 and momentum coefficient 0.3 had lowest error in predicting the flank wear for the testing cases used in that analysis. Moreover, Prasad et al. (2001) presented a paper to develop a method to study the contour of crater wear and measure it in three dimensions. A multilayered perceptron with back-propagation algorithm has been used for tool wear estimation, which could be trained using much less data than that was required in a normal mathematical simulation. Speed, feed, depth of cut and cutting time were used as input parameters and flank wear width and crater wear depth were output parameters. The configuration suited for the present work was at 4-10-10-2, where the ANN values for both flank wear and crater wear were lower compare to the others combination of ANN and the actual measured value. So, it proven that ANN can be a powerful tool to make prediction especially in estimating tool wear characteristic in order to enhancing the machining performance. Elanayar and Shin (1995) proposed a model, which approximates flank and crater, wear propagation and their effects on cutting force by using radial basis function neural networks. The generic approximation capabilities of radial basis function neural networks are used to identify a model and a state estimator is designed based on this identified model. Choudhury et al. (1999) were also used multilayered perceptron in online monitoring of tool wear in turning process. EN24 steel was used as the workpiece material and HSS with 10% Cobalt as the cutting tool. From the results, it shown that the ability of the neural network in generalizing the system characteristics by predicting values close to the actual measured ones even for the cutting conditions not encountered in its training phase. For the experiments used for validating the system, the predicted values were found to be within an error of 6% of the actual measured values. Choudhury et al. (2003) extended discussion by comparing DOE with ANN method in order to establish relationships between temperature and tool flank wear. The amount of flank wear on a turning tool was indirectly determined without interrupting the machining operation by monitoring the temperature at the cutting zone and the surface finish by using a naturally formed thermocouple. They concluded that neural networks perform better than design of experiments technique.

A multilayer feed-forward neural network (MLFF N-Network) algorithm was presented by Liu et al. (1999). The input variables were cutting speed, feed rate, and the monitored cutting force ratio where the output was flank wear. The network was first trained using a set of workpiece material (P20 mold steel) and a tungsten carbide (H13A) cutting tool at various cutting conditions. The algorithm was later successfully verified on-line during turning of the same mold steel at conditions that differ from the data used in training. The on-line estimation of tool wear was still quite satisfactory even when the feeds and speeds changed suddenly during the machining. On-line tests indicate that the proposed tool wear algorithm was quite robust to changing cutting conditions, which frequently occur in practical turning operations. In the same architecture and process machining, Özel et al. (2005) were developed models based on feedforward neural networks in predicting accurately both surface roughness and tool flank wear. In the design of ANN, the major concern was to obtain a good generalization capability. In this study, Bayesian regularization with Levenberg–Marquardt training algorithm was used. The feed rate, cutting speed and cutting length acted as input of ANN structure, while AISI H13 steel as workpiece and Cubic Boron Nitride (CBN) as insert of the experiment. Comparisons between the predictions of tool wear and surface roughness by using both regression-based models are developed and the predictive neural network models are also performed. Predictions with ANN outperform the prediction resulted from regression-based models.

Cutting Force

Modeling of cutting forces has always been one of the main problems in metal cutting theory. The large number of interrelated parameters that influence the cutting forces (cutting speed, feed, depth of cut, primary and secondary cutting edge angles, rake angle, nose radius, clearance angle, cutting edge inclination angle, cutting tool wear, physical and chemical characteristics of the machined part, etc.) makes it extremely difficult to develop a proper model. Although an enormous amount of cutting force related data is available in machining handbooks, most of them attempt to define the relationship between a few of the possible cutting parameters whilst fixing the other parameters. Also, proper mechanisms for extracting general models from existing machining data are still to be developed. In this section, an approach for modeling cutting forces with the help of artificial neural networks was reviewed.

A cutting force model for self-propelled rotary tool (SPRT) cutting force prediction using artificial neural networks (ANN) has been introduced by Hao et al. (2006).The basis of this approach was to train and test the ANN model with cutting force samples of SPRT, from which their neurons relations are gradually extracted out. The inputs to the model consist of cutting velocity, feed rate, depth of cut and tool inclination angle, while the outputs are composed of thrust force (F_x), radial force (F_y) and main cutting force (F_z). The experiment was carried out in turning low carbon steel. Back propagation (BP) algorithm was chosen but seems was often very slow to converge in real practice and was hybrid with Genetic Algorithm (GA). GA was capable of solving wide range of complex optimization problems only using three simple genetic operations (selection, crossover and mutation) on coded solutions (strings, chromosomes) for the parameter set, not the parameters themselves in an iterative fashion. Adopting the GA to select the initialize BP weights containing the information of SPRT cutting force in a large scope, the hybrid of GA–BP ANN model improves the cutting force mapping precision. Hao stated in their discussion, it was confirmed that the hybrid of GA–BP network predicts the SPRT cutting force more accurately than the BP network during the training period, which was very important to real-time control. The SPRT cutting force model with hybrid of GA–BP network can be used to determine the optimum operating parameters for provision of recommendations to engineers and operators or directly control system to keep the SPRT work more efficient.

Aykut et al. (2007) were used ANN for modeling the effects of machinability on chip removal cutting parameters for face milling of stellite 6 in asymmetric milling processes. Cutting forces with three axes (F_x, F_y and F_z) were predicted by changing cutting speed, feed rate and depth of cut under dry conditions. Experimental studies were carried out to obtain training and test data and scaled conjugate gradient (SCG) feed-forward back-propagation algorithm was used in the networks. Main Input parameters for the experiments were the cutting speed, feed rate, depth of cut and cutting forces while cutting forces were used as the output dataset. Results for the values predicted by ANN were very close to experimental values. It was concluded that the best ANN model was a multi-layer model consisting of 3 inputs, 35 hidden neurons and 3 outputs. These results shown that the ANN can be used easily for prediction the effects of machinability on chip removal cutting parameters for face milling of stellite 6 in asymmetric milling processes. Tsao and Hocheng (2008) were conducted an experiment to investigate the thrust force in drilling composite material using ANN. In this study, the feed rate, spindle speed and drill diameter were the input of the ANN structure where radial basis function network (RBFN) and multi-variable regression analysis were used to analyze the data. Table 2 shows the experimental confirmation and comparison with RBFN. It can be seen that the value of RBFN was found more precise and thus demonstrated as a feasible and an effective way for the evaluation of drilling-induced thrust force.

Table 2 :Experimental confirmation and comparison with RBFN

Test no.	**Experiment**	**RBFN**	**Error (%)**
3	65.1	64.8	0.5
4	65.3	64.8	0.8
5	72.8	71.8	1.4
6	57.6	57.3	0.5

Szecs (1999) was developed the cutting force modeling using ANN. Feed-forward multi-layer neural networks, trained by the error back-propagation algorithm was used. For modeling the cutting force components, three-layer feed-forward neural networks were used. The neural networks were trained with the following parameters; tensile strength of the machined material, hardness of the machined material, cutting tool, nose radius, clearance angle, rake angle, major cutting edge angle, minor cutting edge angle, major cutting edge inclination angle, cutting speed, cutting feed, type of machined material, average flank wear, thrust force, radial force, and main cutting force. The calculated cutting force components were then compared to the actual forces given in the training data. The average estimation error was about 9.5%, which was high compared to the 3.5% estimation error of the neural network. So, from the comparison value,it can be concluded that ANN definitely became a powerful tool in order of predicting cutting force in machining.

Material Removal Rate

Material removal is one of the major and oldest shaping processes for the economic production of machine components. Because of the wide use of engineering materials and alloys steels with high hardness in the aerospace industry, fast and precise machining problems have attracted much attention in manufacturing industries for over the last 30 years. Hence rapid failure of cutting tool leads to deterioration of the work piece surface integrity, loss of geometrical tolerances and increase of machining times. The machining time increase is due to downtime in consequence of the exchanging and resetting of cutting tools furthermore reduction of tool life hence ultimately increases of unit cost. Hence to overcome this problem, the application of ANN has been employed recently. A simple neural network model for abrasive flow machining process has been established by Jain et al. (1999). The effects of machining parameters on material removal rate have been experimentally analyzed. Based on this analysis, model inputs and outputs were chosen and off-line model training using back-propagation algorithm was carried out. The objective of the simulation was to first have the system learn the appropriate mappings between input and output variables by observing the training samples. The trained system was then used to determine the input conditions that maximizes material removal rate (MRR) subject to certain constraints. The three layer back-propagation with four inputs, two outputs and nine hidden nodes was employed for neural network. Figure 3 shows the experimental results compared with ANN and theoretical models. The MRR results predicted by simulation using neural network show a good agreement with the experimental results and the results obtained by the theoretical model for a wide range of operating conditions.

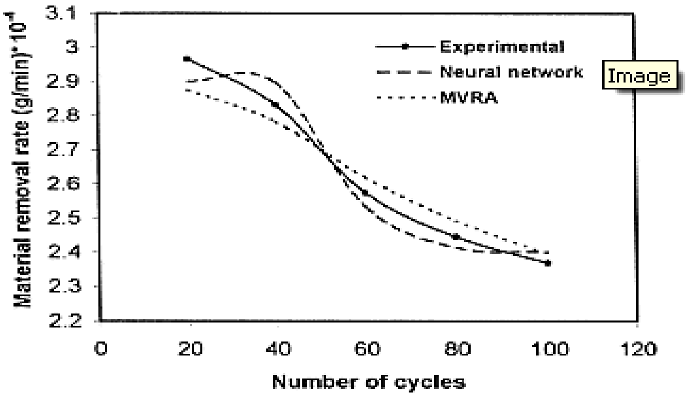

Figure 3: Comparison MRR with ANN application, theoretical and experimental value.

Morover, Tsai and Wang (2001b) were conducted comparison of modeling the material removal rate of the work for various materials considering the change of polarity among six different neural networks together with a neuro-fuzzy network. The six neural networks are namely, the logistic sigmoid multi-layered perceptron (LOGMLP), the hyperbolic tangent sigmoid multi-layered perceptron (TANMLP), the fast error back-propagation hyperbolic tangent multi-layered perceptron (error TANMLP), the radial basis function networks (RBFNs), the adaptive TANMLP, and the adaptive RBFN. Also, the neuro-fuzzy network was the adaptive-network-based fuzzy inference system (ANFIS).The result of ANFIS shows the better prediction than others. It was noted that the ANFIS model was the best, with 16.33% checking error. That means that the predictions of MRR in the EDM process by making use of the ANFIS model was in good agreement with the experimental results.

CONCLUSION

Based on literature review, the ability of ANN technique for the surface roughness, tool wear, cutting force and material removal rate prediction values could be summarized. ANN was able to handle a nonlinear form of modeling that learns the mapping of inputs to outputs, ANN was more successful, when compared to conventional approaches in terms of speed, simplicity and capacity to learn and also require less experimental data. The modeled process and improvements in the behavior of the experimental results are easy to understand in a short time from the neuronal model in ANN. Moreover, ANN allows for simple complementing of the model by new input parameters without modifying the existing model structures and researchers as well as industries have the choice to use and compare different training algorithms such as back propagation algorithm, radial basis algorithm and fuzzy algorithm in ANN to obtain more accurate results of the prediction model.

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