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Prediction of Surface Roughness for Milling Operation Using Artificial Neural Network

By

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Abstract:

In this work different types of artificial neural networks (ANN) models are developed comparing between them for the prediction of best surface roughness (Ra) values in (AL) alloy after milling machine process. The feed forward neural network (FFNN) with different training functions, radial base (RBNN) and generalized regression (GRNN) networks were selected and the data used for training these networks were derived from experiments conducted using CNC milling machine.

The Taguchi design of experiments was applied to reduce the time and cost of the experiments. The six inputs (radial depth of cut, axial depth of cut, cutting speed , feed rate, tool diameter and machine tolerance) selected for the network with the selected output (surface roughness).

Keywords:

Milling – feed forward – radial base – generalized regression – surface roughness.

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1. Introduction:

Milling process is one of the most important and common metal cutting operation encountered for machining parts in manufacturing industry. Surface roughness plays a significant role in determining and evaluating the surface quality of the product.

An artificial neural network (ANN) is a mathematical model or computational model that tries to simulate the structure and/or functional aspects of biological neural networks. It consists of an interconnected group of artificial neurons and processes information using a connectionist approach to computation.

In most cases on ANN is an adaptive system that changes its structure based on external or internal information that flows through the network during the learning phase. Neural networks are nonlinear statistical data modeling tool. They can be used to model complex relationships between inputs and outputs or to find patterns in data. Before a network can perform a useful task, it has to be trained using a set of inputs and known output. Once trained the network is able to give a particular answer for a given set of inputs, [1].

In this paper several ANNs are developed to predict surface roughness on Al alloy after milling process. Six inputs obtained from experimental design technique using orthogonal alloy (OA) to determine the most factors affecting to this process, (radial depth of cut, axial depth of cut, cutting speed, feed rate, tool diameter and machine tolerance) were considered for the development of networks (feed forward back propagation–Radial base and General Regression), [5].

Small depth of cut combined with high feed rate is more efficient than a large depth of cut and slower feed rate. The networks were compared between each other selecting the one that achieved the best performance when comparing the prediction and measured surface roughness value.

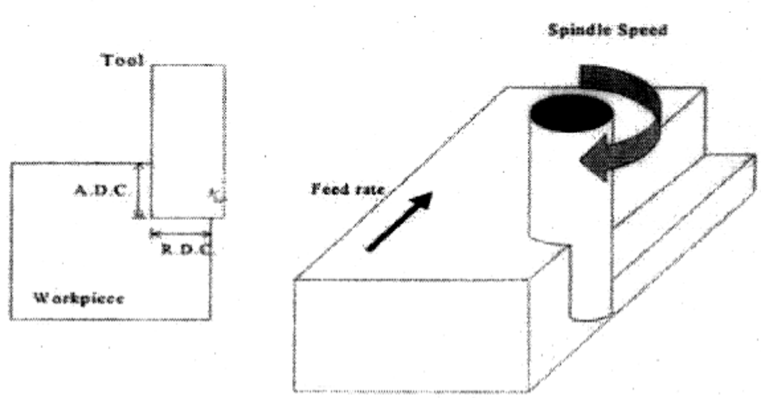


Figure (1): *The milling operation.*

2 Background and literature review

ANNs are an information handling means inspired by biological nerve systems. An ANN is composed of processing elements that are connected in parallel, called neurons Haykin, S. (1999). Every connection contains an adjustable weight. The output comes from the combination of each single neuron's output with these connections. ANNs have several types and applications, such as the self-organising (unsupervised) ANN that is used for classification problems and the supervised ANN that is used for nonlinear multivariate function mapping.

This work uses the supervised ANN for the modelling process. The supervised ANN is trained to acquire knowledge about sophisticated nonlinear functions. ANN then adjusts its weight parameters based on the magnitude of the error difference between the true and ANN outputs.

The algorithms minimise the error function with every new training pattern, such that the error is gradually reduced to a prescribed small value. Tugrul, U. and Yigit, K. (2003) studied the effect of cubic boron nitride tools on surface roughness. A predictive modelling approach is presented utilising computational static Neural Networks (NNs). One of the objectives is to develop Back Propagation (BP) NNs to predict the both surface roughness and tool flank wear of hardened steel parts.

Regression models are then developed to capture specific process parameters. Some experiments are used to train the neural model. The trained model is used to predict the surface roughness and flank wear under different cutting conditions. Bayesian regularisation is used to avoid certain system configurations for the input, hidden and output layers.

Another BP NN model is used to predict the tool flank wear in machining stainless steel using turning lathe Chien, W-T. and Tsai, C-S. (2003) . The predictive values are used as a constraint to optimise some cutting conditions based on the maximum metal rate.

Feeding experiments are planned using the Taguchi method and OAs Ross, P.J. (1988).Genetic Algorithms (GAs) and the Taguchi method are employed to design the predictive model parameters and optimisation is used to minimise the prediction errors. The results indicate that the tool flank wear prediction accuracy ranges from 6.64%–8.6%.

A new approach using NNs for flat end milling operation was presented El Mounayri, H., Kishawy, H.A. and Tandon, V. (2002). The feed rate, spindle speed and radial depth of cut are used as input parameters. FFD techniques are used to plan the experiments that are needed for training. Four OAs, specifically, L9 OA, L27 OA, L27 OA (extended range) and L36OA, are employed. A comparison among these arrays is carried out. The L36 OA model results in a better predictive model.

An online predictive model for the surface roughness in turning operations was presented using an Adaptive Neuro-fuzzy Inference System (ANFIS) and computer vision Ho, S-Y., Lee, K-C., Chen, S-S. and Ho, S-J. (2002) . The model aims at precisely predicting the features of surface roughness under certain cutting parameters. The experimental results demonstrate better modeling and prediction accuracy than polynomial network-based models. Sukthomaya,W.andTannock,J.(2005)concentrated on NN methods to model complex manufacturing processes. The study summarized the use of NNs for process modeling and provided training guidelines. A forming process was used for demonstration.

In another study, they described the methods of manufacturing process optimization using Taguchi experimental design methods with historical process data. Two separate techniques are employed. The retrospective Taguchi approach selects the designed experiment data from a historical database. The other approach is the regular NN. Both techniques require the availability of process databases. The study considered only two levels of OAs. This means that only linear relationships can be investigated.

The cutting process is assumed to be orthogonal and the material is removed by a cutting edge that is perpendicular to the direction of the relative tool-part motion. Using such a simplification, the cutting force is uniform along the cutting edge, the resulting chip is uniform flat and the resulting stress and shear distributions along the stress and shear planes are uniform. In addition, machine vibrations, spindle run-out and thermal effects are ignored.

A combination of Response Surface Methodology (RSM) and ANN is given (Erzurmlu, T. and Oktem, H. (2007)) to predict the surface roughness of mold surfaces. Several process variables are considered. The statistical DOEs are used to plan experimentation. Data are fed into a Feed Forward (FF) NN that is based on BP architecture. The two models show close agreement.

The literature review shows that past studies focused on:

- Advanced mathematical models that are based on the physics and geometry of metal cutting
- Implementation strategies which allow faster and easier solutions of nonlinear equations.

Accordingly, NN, with the exception of expensive modeling costs, is considered an excellent modeling approach. Several studies attempt to compare neural models and traditional techniques. Complete considerations of dynamic effects are still challenges to researchers. The cutting force prediction, surface roughness estimation and wear rate calculations are just some concerns. However, neural modeling still faces unanswered questions, such as:

- over fitting and under fitting of models
- the relative merit techniques of Radial Basis (RB), FF and probabilistic models, *etc*.
- insufficient data and information.

Al-Ghanim, A. (2002) employed ANNs to provide efficient solutions for decision-making purposes in Computer Integrated Manufacturing (CIM). Self-organizing NNs are used to select the milling machining parameters. Vague problems are handled using the proposed approach, as full knowledge of the output data is not needed during the training phase. Model calibration uses a small portion of data. The size of this portion is still unknown. Tugrul, U. and Yigit, K. (2003) pointed to two key issues: the design input in a feature-based model and the acquisition and representation of process knowledge, especially empirical knowledge.

The paper presents a state-of-the-art review in CIM using NN techniques, Four issues are discussed:

1- the topology of the NNs
2 -input representation
3 -the training method
4 -the output format.

Lee, C. and Yung, S. (2004) presented a framework for modeling complex manufacturing processes using fuzzy NNs. A hierarchical structure that is based on Fuzzy Basis Function Network (FBFN) is proposed to construct the comprehensive models of complex processes. A new Adaptive Least Squares (ALS) algorithm, based on the least squares method and GAs, is proposed for autonomous learning and the construction of FBFNs. The proposed method is implemented for the surface grinding process. The accuracy of the developed models is validated through a comparison with grinding experiments .Jeon, S.S., Duk, M.L., Ill-S.K. and Seung, G.C. (2005)pointed out that the automation of steel rolling through mathematical modeling is very complex due to many interacting decision variables. An online NN is developed to improve the force prediction in a hot rolling mill. Several NN designs are developed in terms of the number of neurons and epochs. In all these models, the number of hidden layers is taken as one. Tangential sigmoid nonlinear functions and Levenbarg and Marquardt are used as learning algorithms. Leo, C-K. and Bruce, S.C. (2005) employed ANNs to establish the relationship between the operating parameters and the bump properties with the experimental data.

An optimization scheme is developed for the evaluation of the optimal operating condition of a gold stud bumping process in a typical manufacturing foundry. The process model is established to describe the relationship between the operating factors and bump properties. Three optimization process cases are solved using the developed model. Jangsombatsiri, W. and Porter, J. (2006) employed ANN to the laser part-making process.

Training, validation and the testing of data are typical phases in NN modeling. Two performance measures are used for assessment; these are the Mean Square Errors (MSEs) and the R coefficient. A single-output ANN model is compared with linear regression models and is reported superior over the domain employed. The best structure for the standard performance measures is then given.Mu, C. and Taho, Y. (2002) developed a BP NN. Mathematical models are formulated using the mapping functions that were generated from NN metamodels. The optimization model is solved by a stochastic local search (Simulated Annealing) to obtain an optimal configuration. The solution space is exploited to escape the local optima Haber, R. and Alique, A. (2003) developed an intelligent supervisory NN system to predict the tool wear in machining processes. Two process parameters are investigated and the model describes the output dynamic responses. Three tool conditions are investigated (new, half worn and worn tools). Wear is a physical phenomenon and the development of an advisory system is one aspect in the prediction of nonlinear model performance

3- Surface roughness

The surface parameter used to evaluate surface roughness in this study is the roughness average (Ra). This parameter is also known as the arithmetic means roughness value, arithmetic average (AA), or centerline average (CLA).

R_a is recognized universally as the commonest international parameter of roughness. The average roughness is the between the roughness profile and its center line or the integral of the absolute value of the roughness profile high over the evaluation length. There fore, R_a is specified by the following equation: (19)

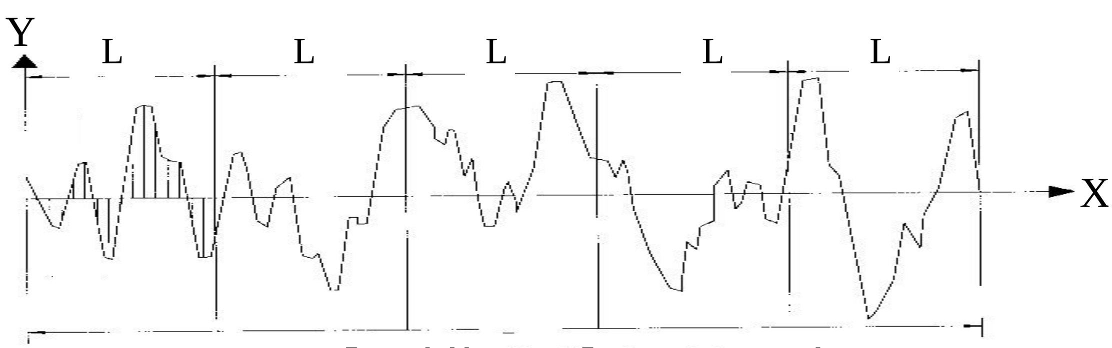
$$R_a = \frac{1}{L}\int_0^L Y(X)dx, \quad (1)$$

When evaluation from digital data, the integral is normally approximated by a trapezoidal rule:

$$\text{Ra} = \frac{1}{2}\sum^{m} \int_{i} \gamma_a \quad \left| \begin{matrix} \text{y} \\ \text{i} \end{matrix} \right| \quad (2)$$

Where R_a is the arithmetic average deviation from the mean line (Yi), is the sampling length, and Y is the ordinate of the profile curve.

Graphically, the average roughness is the area between the roughness profile and its center line divided by the evaluation length (normally five sample lengths with each sample length equal to one cutoff).(10)



Where:

Y : Profile curve.

X : Profile direction

Z : Average roughness height

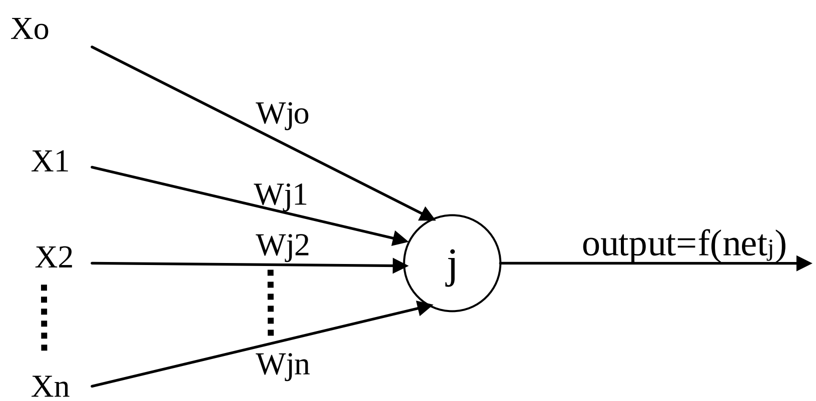
L : sampling length

4- Basics of artificial neural networks:

4-1 Individual Neuron

Te individual processing unit in ANNs receives input from other sources or output signals of other units and produces an output. The input signals (X_i) are multiplied with weights (w_{ji}) of connection strength between the sending unit (i) and receiving unit (j). The sum of the weighted input is passed through an activation function. The output may be used as an input to the neighboring units or units at the next layer. Assuming the input signal by a vector X (X_1, X_2 ….X_n) and the corresponding weights to unit (j) by W_j (W_{j1}, W_{j2} ….. W_{jn}). **(21)**
The net input to the unit (j) is given by Equation 3.
The weight W_{j0} (= b) is a special weight called bias whose input signal is always +1.

$$net_j = \sum_n wjnXn + W_{jo} = w_j X + b \qquad (3)$$



Figure(3): *An Individual unit in a neural network*

In General, a neural network is characterized by the following three major components:

- The computational characteristics of each unit (activation function).
- The network. Architecture.
- The learning algorithm to train the network.

4-2 Activation function:

The computed weighted sum of input is transformed into an output value by applying an activation function. In most cases, the activation function maps the net input between -1 to +1 or to 1. This type of activation function is particularly useful in classification. Tasks in cases where a neural network is required to produce any real value, liner activation function may be used at the final layer. Effectively reduce to a single layer network. This type of net work is incapable of solving nonlinearly separable problems and has limited capability. Since the most real world problems are nonlinearly separable, nonlinearity in the intermediate layer is essential for modeling complex problems. There are many different activation functions proposed in the literature that are often chosen to be monotonically increasing functions**.(20)**

4-3 Network Architecture:

Having defined an individual neuran, the next step is to connect them together. A neural next work architecture – represents a configuration indicating how the units are graped together as well as the inter connection between them. There is much different architecture reported in the literature, however. Most of these can be divided into two main broad categories: feel forward and feed back, in feed forward architecture, the information signal always propagates towards the forward direction while in feed back architecture the final output are a given feedback at the input layer, (17).

Table (1) *commonly used activation function.*

Activation function	Mathematical expression
Linear	F (x) = x
Logistic sigmoid	$F(x) = \dfrac{1}{1 + \exp(-x)}$
Logistic	F(x) = tanh (x)
Gaussian	$F(x) = \exp(-X2/26^2)$

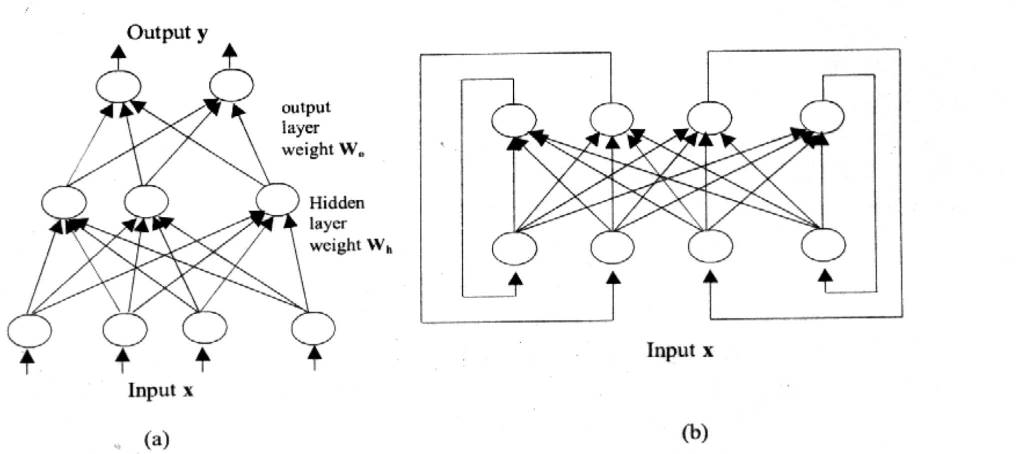


Figure (4) ***(a)*** *feed forward architecture –* ***(b)*** *feed back Architecture*

The first layer is known as input layer the last as output layer and any intermediate layer (s) as hidden layer (s). A multiple feed forward layer can have one or more layers of hidden units. The number of units at the input layer and output layer is determined by the problem at hand. Input layer units correspond to the number of independent variables while out put layer units correspond to the dependent variables or the predicted values, (18). While the numbers of input and out units are determined while the numbers of hidden layers and the units in each layer may vary. There are no widely accepted rules for designing the configuration of a neural network. A network with fewer than required number of hidden units will be unable to learn the input – output mapping, whereas too many hidden unit will generalize poorly of any unseen data, (16).

4-4 Learning Algorithms:

A neural network starts with a set of initial weights and then gradually modifies the weights during the training cycle of settle down to a set of weights capable of realizing the input-output mapping with either no error or a minimum error set by the user. Learning in neural networks can be supervised or unsupervised. Supervised learning includes back propagation and its variants, Radial Basis function neural network, (9).

(RBFNN) probabilistic neural network (PNN). Generalized. Regression Neural Network (GRNN) and soon, in supervised learning an input datum is associated with a known output, and training is done. In pairs, in supervised learning, for example, self organizing map (SOM) Adaptive Resonance Theory (ART) and soon, is used when training sets with known outputs are not available, in the following, we describe some of the widely used ANN learning algorithms, (3).

4-5 Back propagation Algorithm:

A recent study has shown that approximately 95% of the reported. Neural network industrial applications utilize multilayer feed – forward neural networks with back propagation learning algorithm. Back propagation is a feed – forward network that updates the weights iteratively to map a set of input vector (x_1, x_2,…. x_p) to a set of corresponding output vector (y_1,y_2,….y_p). The input x_p corresponding to pattern or data point "p" is presented to the network and multiplied by the weights. All the weighted inputs to each unit of the upper layer are summed up, and produce an output governed by the following equation.(2)

$$\gamma = f(W_0 h_p + \theta_0) \tag{4}$$

$$h_p = f(wh\chi_p + \theta_n) \tag{5}$$

Where w_0 and w_n are the output and hidden layer weight matrices, h_p is the vector denoting the response of hidden layer for pattern "p", θ_0 and θ_n are the output and hidden layers bias vectors, respectively and (f) is the sigmoid activation function. The cost function to be minimized in standard back propagation is the sum of squared error defined as:(25)

$$\mathrm{E} = \frac{1}{2}\Sigma\left(\tau_p - \gamma_p\right)^T\left(\tau_p - \gamma_p\right) \tag{6}$$

Where τ_p is the target output vector for pattern "p". The algorithm uses gradient descent technique. To adjusts the connection weights between neurons. Denoting the fan-in weights to a single neuron by a weight vector W, its update in the t-th epoch is governed by the following equation.

$$\Delta\omega_1 = -\eta\nabla\mathrm{E}(\omega)\big|\omega = \omega(\tau) + \alpha\Delta\omega_1 - 1 \tag{7}$$

The parameters and α are the learning rate and the momentum factor, respectively. The learning rate parameter controls the size in each iteration, for large-scale problems. Back propagation learn very slowly and its convergence. Largely depends on choosing suitable values of η and α by the user.

5- Experimental data for training and validation:

The machine used for this work is FADAL 4 axis CNC milling machine and the work piece material considered was Aluminum 7075TG.The cutting parameters selected as control factors of the milling process where the tool diameter depths of cul (radial and axial), cutting speed, feed rate and machine tolerance, (8). The level of these factors are showing in the table below:

Table (2) *factors levels*

Factors	Level 1	Level 2	Level 3
A: radial depth of cut	0.04 (in)	0.06	0.08
B: axial depth of cut	0.012 (in)	0.020	0.028
C: cutting speed	1500 (rpm)	2500	3500
D: Feed rate	20(inpm)	30	40
E: Tool diameta	0.75(in)	1	1.5
F: machining tolerance	0.001 (mm)	0.0055	0.01

The full factorial design:- FFD = 3^{6} = 729 experiments (27)

In these work we use fractional factorial design $\frac{1}{9}$ FFD = 81 experiments (28)

6- The result after training using L 81 orthogonal array are shown in the following table and graphs:

6-1-Mean square error (MSE)

From mean square error (MSE) table above we note that the Radial basis Neural Network has the best values of mean square error for this process.

Table (3)*Mean square error*

MSN of ANN function					
FFBP				Gener reg	R basis
trainlm	traingd	trainbr	trainscg		
0.9814	2.122	0.9499	1.374	2.136	0.6382

6-2 Relation between Surface Roughness values from experiments (Ra exp), and Surface Roughness values from Neural Networks(Ra NN)

a) <u>Ra exp. compared with Ra value from FFbp with train BR</u>

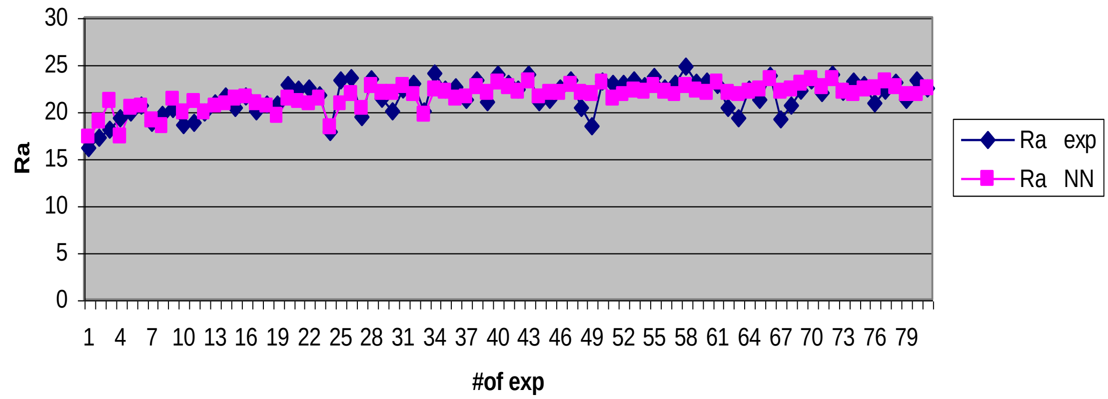


Fig (5) *ffbp (trainBR)*

(b) <u>Ra exp. compared with Ra value from FFbp with train GD</u>

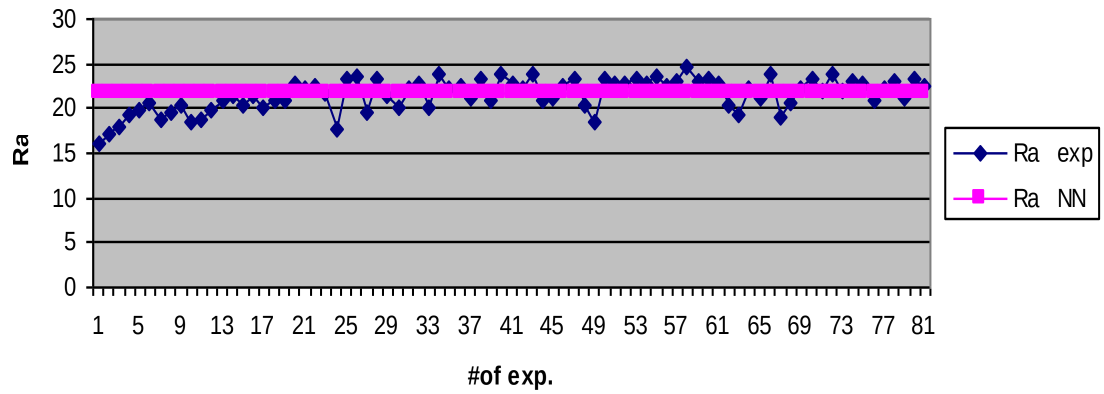


Fig (6) *ffbp (trainGD)*

(c) <u>Ra exp. compared with Ra value from FFbp with train LM</u>

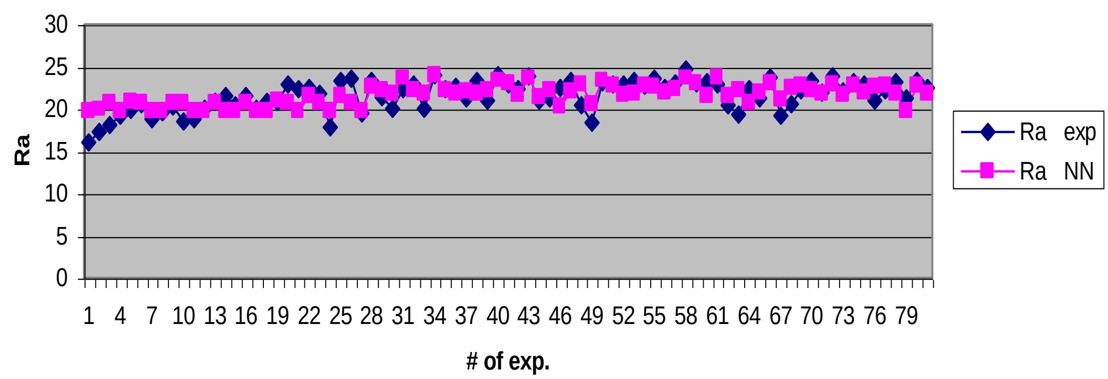


Fig (7) *ffbp(trainLM)*

(d) Ra exp. compared with Ra value from FFbp with train SCG

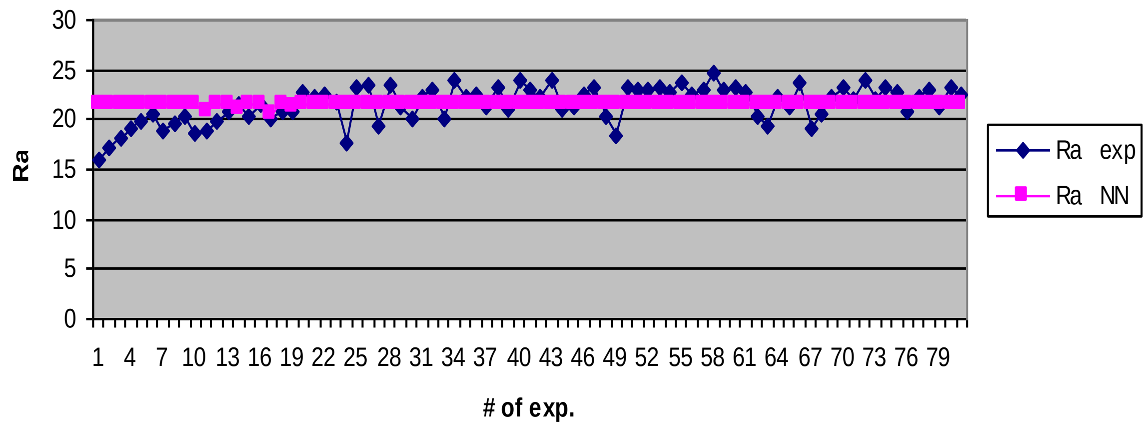


Fig (8) *ffbp(trainSCG)*

(e) Ra exp. compared with Ra value from FFbp with train GRNN

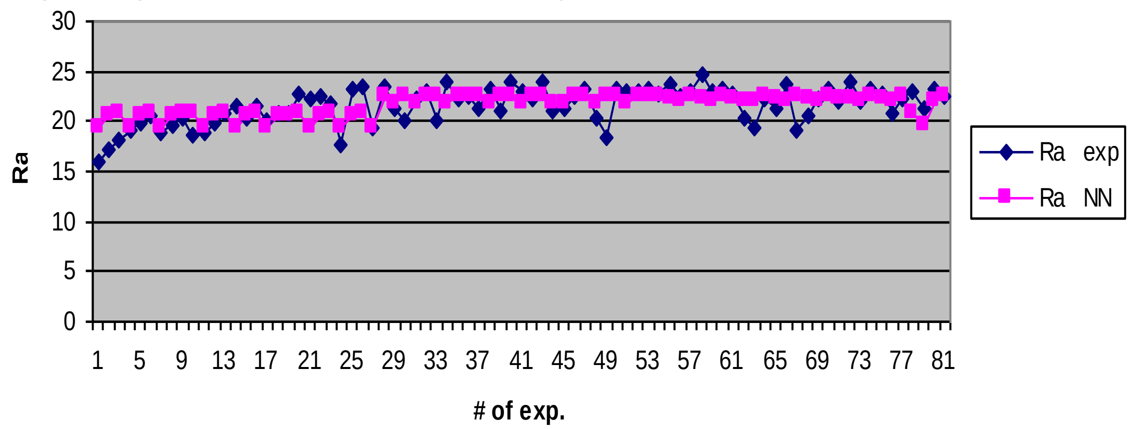


Fig (9) *ffbp(trainGRNN)*

(f) Ra exp. compared with Ra value from FFbp with train RBNN

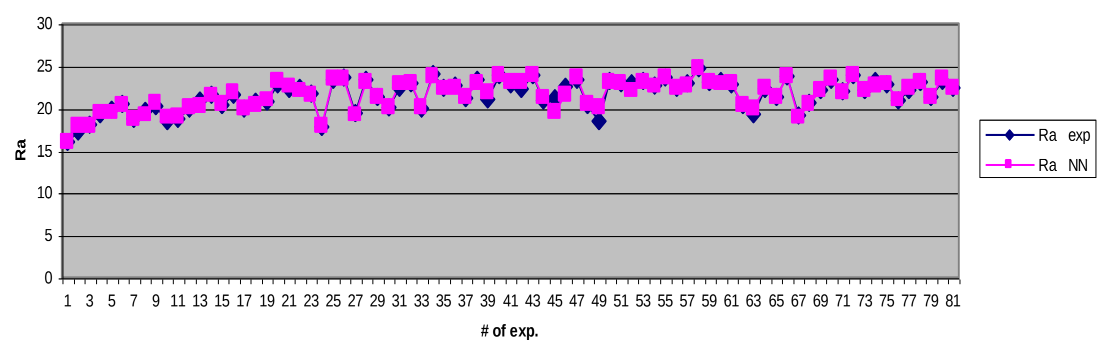


Fig (10) *ffbp(trainRBNN)*

7- Result and Discussion:

The 81 experiments was used to study the effect of the 6 parameters (radial depth of cut, axial depth of cut, cutting speed, feed rate, tool diameter and machine tolerance) obtained from experimental design technique using orthogonal allay (OA) to determine the most factors affecting to this process on the surface roughness of work piece

This work the different types of ANN approach were trained to predict the surface roughness. The types of ANN were used are feed forward back propagation with various learning methods (L M , S C G ,GD and RR) , radial basis NN and generalized regression NN .By using MATLAB NNTOOL the networks are trained with only 60% of data collected or 49 experiment 20%corresponding to validation set or 16 experiments and20% corresponding to test. We note that the biggest advantage of ANN is simplicity and speed of calculations and Radial Basis NN is the best result to prediction surface roughness, compared with other types of NNs.

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