# Surface roughness prediction during grinding: A Comparison of ANN and RBFNN models

NIKOLAOS E. KARKALOS
Section of Manufacturing Technology, School of Mechanical Engineering
National Technical University of Athens
Heroon Polytechniou 9, 15780, Athens
GREECE
nkark@mail.ntua.gr

JÁNOS KUNDRÁK
Institute of Manufacturing Science,
University of Miskolc
Miskolc-Egyetemváros H-3515
HUNGARY
kundrak@uni-miskolc.hu

ANGELOS P. MARKOPOULOS
Section of Manufacturing Technology, School of Mechanical Engineering
National Technical University of Athens
Heroon Polytechniou 9, 15780, Athens
GREECE
amark@mail.ntua.gr http://users.ntua.gr/amark/

*Abstract:* - Grinding is one of the most widely employed manufacturing processes when accurate finishing of workpieces is required. In order to investigate the effect of processing parameters to grinding performance, soft computing methods constitute a reliable and economical alternative to other simulation methods, such as the Finite Element Method (FEM). In this study, a comparison between classical Artificial Neural Network (ANN) models and Radial Basis Function Neural Network (RBFNN) models is conducted for a case of face grinding of various types of steel workpieces, cutting wheel types and depths of cut and their performance towards the prediction of surface roughness is evaluated. Results indicate that RBFNN can provide better results than classical ANN networks and adequately model the surface roughness during grinding processes.

*Key-Words:* - grinding, finishing operations, manufacturing, surface roughness, artificial neural networks, radial basis functions, soft computing

## 1 Introduction

Grinding is considered as one of the well-established manufacturing processes in industrial applications. Grinding is classified among abrasive machining processes and although it is primarily intended for use in finishing applications, it can be employed for bulk material removal as well. As a finishing process, grinding is often preferred due to its ability to produce high dimensional accuracy and workpiece surface quality whereas as a bulk material removal process it can efficiently machine hard-to-cut or very brittle materials.

Analysis of grinding process is essential to allow for the experiments to be conducted under optimum conditions or to identify and explain the underlying mechanisms responsible for thermo-mechanical phenomena that occur during this process. Analysis can be conducted either by means of experimental measurement techniques, or by means of numerical and soft computing techniques such as the Finite Element Method [1-3], Artificial Neural Networks [4], regression techniques [5], other statistical methods [6] etc. One important advantage of non-experimental methods is significant reduction of cost and time and so they are increasingly employed along with experimental studies.

Some examples of ANN applications concerning machining processes are described hereafter. Özel and Karpat [7] employed ANN to model surface roughness and tool wear in hard turning. Ezugwu et

al. [8] used ANN to model high speed machining process of Inconel 718 alloy. Zuperl et al. [9], Adesta et al. [10] and Al Hazza et al. [11] employed also ANN to model end-milling processes. Studies using RBF neural networks in machining process simulations are significantly fewer than these using Multi-Layer Perceptron (MLP) networks as the aforementioned works, according to Pontes et al. [12].

Gong et al. [13] employed RBFNN with various spread factor values to predict cutting consumption. Compared to results produced with MLP networks, network error and fit values were considerably better in cases conducted with RBF models. Parikh and Lam [14] conducted a study to determine optimal parameters during abrasive water jet machining using Back-Propagation (BP) and RBF neural networks as well as regression models. They concluded that RBF networks outperformed other models and that this type of ANN has great potential. Dashtbayazi and Ghanbarian [15] conducted comparison between RBF networks and MLP networks with a single hidden layer and found that MLP networks outperformed RBF ones.

In the current study, several artificial neural networks models are created to predict surface roughness in cases of surface grinding of various steel workpieces. Furthermore, RBF networks are created and compared to MLP in order to determine optimal predictive model. Performance of created models is assessed by prediction error values and actual to predicted output correlation. Conclusions are drawn concerning the efficiency and applicability of these models.

## 2 Artificial Neural Networks

### 2.1 Multi-layer perceptron models

MLP neural networks consist of a number of neurons interconnected via links called synapses. As, it can be seen in Fig.1, the neurons are ordered in parallel rows called layers; the first and the last layer constitute the input and output layers, respectively, and are related to the number of input and output parameters of the model. The inner layers are called hidden layers and are employed for the propagation of data between input and output layers, i.e. in the case of feed-forward networks. The total number of layers and neurons in each layer define the architecture of the network. The optimal architecture of the network is essential to be determined as increased number of neurons leads to increased computational cost.

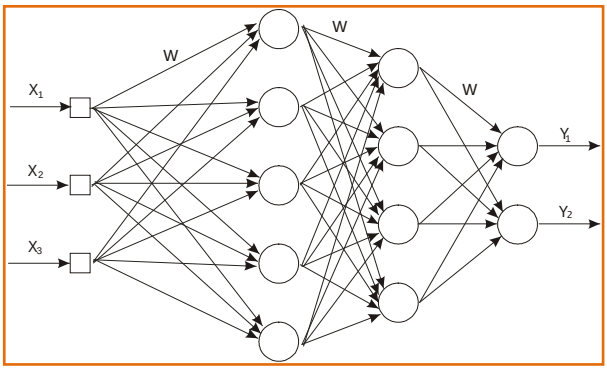

Fig.1 Architecture of an MLP network

The predictive ability concerning a specific problem is gained by the ANN through the training process. The training process consists essentially of the adjustment of weight coefficients until training error is minimized. Training error can be calculated in several ways but often the Mean Squared Error (MSE) between actual and predicted output is employed. In most cases, the mean square error of the network's response to a vector p is calculated, namely:

$$E_p = \frac{1}{2}\sum_{i=1}^{l}\left(d_{p,i} - o_{p,i}\right)^2 \quad (1)$$

where $o_{p,i}$ are the values of the output vector which occur for the input vector p and $d_{p,j}$ are the values of the desirable response corresponding to p.

Training is an iterative process during which the error is propagated backwards from the output to the input layer and weight coefficients are updated at each iteration. The goal of the process is to repeat the procedure until MSE becomes zero. Each time that the program passes through all pairs of training vectors an epoch is completed and training usually ends after reaching a great number of epochs.

### 2.2 Radial Basis Function Neural Networks

RBF neural networks are considered as a special case of feed-forward neural networks. In this type of neural networks a single hidden layer is employed, as it can be seen in Fig.2, and so they have a simpler architecture and generally lower computational cost. Nevertheless, their predictive ability is no inferior to that of other neural network types.

Generally, the basic features of MLP networks apply also to RBF networks and the main differences are the application of a radial basis function to neuron input after summation is performed and the use of Gaussian function as activation function. Due to the use of a Gaussian

function, spread parameter (σ) choice is important element for the performance of these networks.

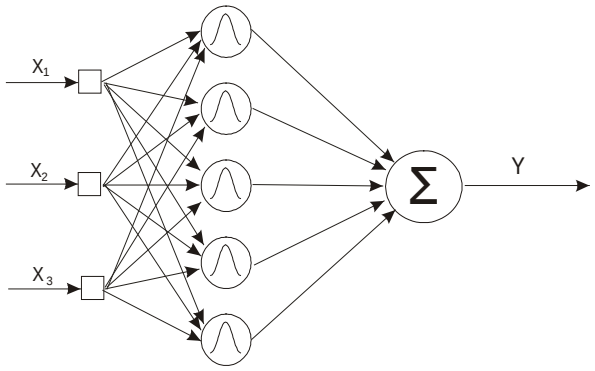


Fig.2 RBF neural network model

## 3 Methodology

MLP and RBF neural network models are created for the prediction of surface roughness in surface grinding experiments. For all ANN models, three inputs, namely workpiece material type, grinding wheel type and depth of cut are employed along with a single output variable, surface roughness, Ra.

Surface roughness, is a key factor in machining. It is usually employed to evaluate and determine the quality of a product. It influences several attributes of a part such as fatigue behavior, wear, corrosion, lubrication and surface friction. Surface roughness refers to deviations from the nominal surface of the third up to the sixth order. First and second order deviations refer to form and waviness respectively. Third and fourth order deviations refer to periodic grooves, cracks and dilapidations, which are connected to the shape and condition of the cutting edges, chip formation and process kinematics. Fifth and sixth order deviations refer to workpiece material structure, which is connected to physical chemical mechanisms acting on a grain and lattice scale. Generally surface roughness can be described as the inherent irregularities of workpiece left by various machining processes. The most common way to describe surface roughness is the average roughness which is often quoted as Ra.

Average roughness is defined as the arithmetic value of the deviation of profile from centerline along a sampling length. It is calculated as:

$$Ra = \frac{1}{l}\int_0^l |y(x)|dx \qquad (2)$$

where l is the sampling length and y is the ordinate of the profile curve. Surface roughness is influenced by controlled machining parameters, such as feed rate, grinding wheel speed, depth of cut, as well as by non-controlled factors, such as non-homogeneity of workpiece and tool, tool wear, machine motion errors, formation of chips and unpredictable random disturbances.

Values of surface roughness are obtained for a total number of 72 cases from a previous study [16] and range of input variables is specified in Table 1.

Table 1. Description of input parameters employed in ANN models

| | |
|---|---|
| Workpiece material | 100Cr6<br>C45<br>X210Cr12 |
| Grinding wheel type | 6 types with variable bonding material |
| Depth of cut | 0.01 mm<br>0.02 mm<br>0.03 mm<br>0.05 mm |

Workpiece material type and grinding wheel type are coded as 1-3 and 1-6 respectively for reasons of simplicity. It is considered that this approach is not affecting ANN results [16] as for all input and output variables a normalization process is applied before their use in the training process of ANN models in order for their values to lie in the 0-1 range.

All other process parameters were kept fixed in the experiments such as workpiece speed $v_w$ of 8 m/min, cutting speed $v_c$ of 28 m/s, wet machining conditions. All grinding wheels are made of $Al_2O_3$ with the same diameter $d_s$ of 250mm and width $b_s$ of 20 mm and various types of bonding.

As for MLP simulations, cases with 4 different training algorithms, namely conjugate gradient (CG) with Powell-Beale restarts (CG(B)), CG with Fletcher-Reeves updates (CG (F)), CG with Polak-Ribiére updates (CG (P)) are employed along with the Levenberg-Marquardt (LM) method and various networks architectures, i.e. up to two layers and 10 neurons, are investigated. As for RBF simulations, cases with variable number of neurons, ranging from 5 to 60 in the hidden layer and spread factor values between 0.25 and 2.00 are considered.

The general approach of the problem of determining the optimal neural network is conducted in various steps. The stages of this approach contain at first the determination of optimal training algorithm in MLP networks and the determination of optimal network architecture of MLP networks. In order to reduce the effect of initial weight values to the results, the calculations

for each case are repeated five times with different initial weights and the results of the best performing cases are selected.

## 4 Results and Discussion

### 4.1 Choice of training algorithm for MLP models

The initial stage of the methodology employed in this study consists of the determination of optimum training algorithm for the given set of input/output data. This step is fundamental as it can lead to a considerable decrease of computational cost for the next set of ANN models development. In order to ensure that judgment is based on results produce by diverse types of MLP networks, both single and two-layer networks are chosen, with 5 different cases in total, as presented in Table 2.

Table 2. Characteristics of studied cases

| Case | 1st hidden layer neurons | 2nd hidden layer neurons |
|---|---|---|
| 1 | 4 | - |
| 2 | 9 | - |
| 3 | 4 | 7 |
| 4 | 6 | 10 |
| 5 | 9 | 5 |

As it was mentioned before, the various ANN models will be assessed in terms of MSE and correlation coefficient R mainly during test stage of training process. At this step, the cases using 5 different network architectures, presented in Table 2, with each one of the four training algorithms are considered.

From the results of Fig.3, it is first observed that in many cases the developed models performance is relatively low, especially in terms of correlation coefficient, as values lie mostly below 0.5; a perfect fit is indicated by values close to 1. MSE error in all cases is within acceptable range, namely 0.02-0.06 during test process. However, there are several differences concerning the performance of each algorithm that can be observed.

From the results in Fig.3, it is clearly observed that MLP networks trained with LM algorithm have better performance at almost every case in terms of correlation coefficient and also relatively small MSE test error values at most cases. So, cases run with LM are performing better in terms of predictive ability and thus LM is selected as training algorithm for the cases that will be used to determine optimal network architecture.

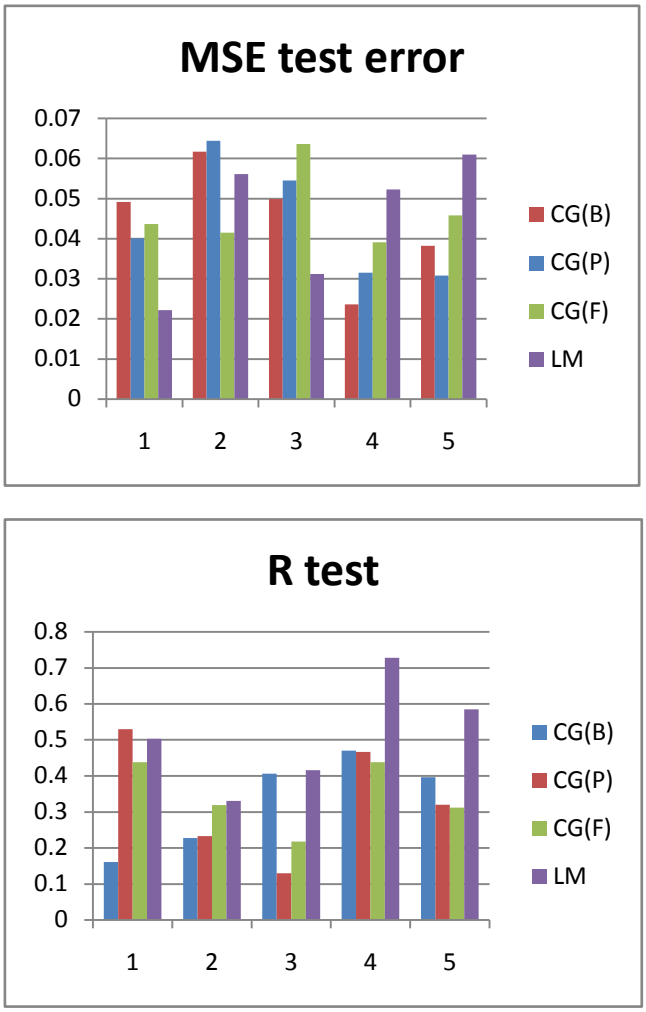


Fig.3 Comparison of MSE test error and correlation coefficient values for each algorithm

### 4.2 Choice of training architecture for MLP models

After it was determined that LM algorithm can produce more accurate results, a new set of models was developed and tested in order to determine optimum network architecture. Several combinations of number of neurons and number of hidden layers are considered.

At first, it was found that the network with 6 neurons in a single layer is the best performing network with single hidden layer and the network with 9 neurons in the first and 7 neurons in the second hidden layer, respectively, is the best performing network with 2 hidden layers, as presented in Table 3. Among these networks, the second network is clearly better both in terms of MSE error and correlation coefficient, so it is

determined that this is the optimal architecture. Moreover, the difference in training speed between the two networks is not largely different, so it is considered that it will not be the decisive factor in the selection of optimal network architecture.

Table 3. Results of best cases conducted with one and two hidden layers

| No of 1st-2nd hidden layer neurons | 6 | 9-7 |
|---|---|---|
| MSE train | $1.43 \times 10^{-2}$ | $6.25 \times 10^{-3}$ |
| MSE test | $5.71 \times 10^{-2}$ | $2.44 \times 10^{-2}$ |
| R train | $8.12 \times 10^{-1}$ | $7.54 \times 10^{-1}$ |
| R test | $5.46 \times 10^{-2}$ | $7.64 \times 10^{-1}$ |

Nevertheless, from the above mentioned results, it becomes obvious that MLP models do not provide highly reliable results as correlation coefficient values, maximum being 0.76 at test process, indicate a medium fit between actual and predicted outputs. Thus, the next step originally proposed, namely testing of RBF networks, is considered essential.

### 4.3 RBF neural networks models

As MLP models proved not adequate enough, several RBFNN models are developed to determine whether this type of ANN can simulate the experimental data more accurately. The parameters that were varied among the cases were the maximum number of neurons and spread parameter value. From the results obtained, in total 45 cases, some indicative results are presented in Table 4.

Table 4. Results of cases conducted with RBF models

| Neurons/ spread | MSE train error | MSE test error | R train | R test |
|---|---|---|---|---|
| 50/0.250 | 0.0033 | 0.0131 | 0.9602 | 0.8802 |
| 50/0.500 | 0.0036 | 0.0142 | 0.9588 | 0.8768 |
| 60/0.250 | 0.0021 | 0.0084 | 0.9747 | 0.8942 |
| 60/0.500 | 0.0033 | 0.0068 | 0.9735 | 0.8932 |
| 60/1.00 | 0.0020 | 0.0081 | 0.9767 | 0.8960 |
| 60/2.00 | 0.0047 | 0.0187 | 0.9426 | 0.8648 |

From Table 4, the optimal RBF model is determined to be a network with 60 neurons in the hidden layer and spread parameter equal to 1.00. Generally, in cases with over 40 neurons it was shown that networks with spread parameter values lower or equal 1.00 were producing better results.

### 4.4 RBF neural networks models

The final step is the comparison of best performing MLP and RBF models, in order to determine the overall best performing network. The characteristics and results of two models are presented in Table 5.

Table 5. Comparison of best performing MLP and RBF models

| | Optimum MLP | Optimum RBF |
|---|---|---|
| MSE train error | 0.00623 | 0.002 |
| MSE test error | 0.0244 | 0.0081 |
| R train | 0.754 | 0.977 |
| R test | 0.764 | 0.896 |

The best performing case of RBF model produces significantly better results both in terms of MSE error and correlation coefficient values, so it is considered as optimal network. As the cases were on the same PC, a comparison in terms of computational time can also be conducted. More specifically, RBF network was trained in 2.44 s whereas MLP network in 1.73 s. However, given that RBF network is shown to produce results close enough to experimental ones, this difference in speed is not considered large enough to justify the selection of MLP networks as more preferable model type.

## 5 Conclusions

In this study, ANN and RBFNN soft computing models were employed for the case of surface roughness prediction during grinding. A comparison of the results between the two methods was also conducted and useful conclusions were drawn:

- The optimum parameters for the ANN models were determined by testing 4 different training algorithms and various network architectures with one and two hidden layers. The Levenberg-Marquardt algorithm was found to be the best performing training algorithm and 3-9-7-1 was found to be the optimum network architecture.
- ANN models exhibit rather moderate levels of accuracy, with R values not exceeding 76% and MSE test error of $2.44 \times 10^{-2}$ for the model with the optimum parameters.
- Compared to ANN model results, RBFNN are considered superior, as the best RBFNN model exhibited high levels of accuracy. More specifically, R value of 90% and low MSE test error values of the order of 0.0081.

The aforementioned results indicated that RBFNN are a promising soft computing method for machining processes simulation and further testing of this method in future works is considered to provide more reliable and accurate models.

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