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RESEARCH ARTICLE

On the Modeling of Surface Roughness and Cutting Force when Turning of Inconel 718 Using Artificial Neural Network and Response Surface Methodology: Accuracy and Benefit

Hamid Tebassi[1*], Mohamed Athmane Yallese[1], Ikhlas Meddour[1], Francois Girardin[2], Tarek Mabrouki[3]

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Abstract

This paper is an attempt to compare artificial neural networks and response surface methodology for modeling surface roughness and cutting force in terms of better coefficient of determination (R^2), lower root mean square error (RMSE) and model predictive error (MPE). Models were developed based on three-level Box-Behnken design (BBD) of experiments with 15 experimental runs composed of three center points, conducted on Inconel 718 work material using coated carbide insert with cutting speed, feed rate and depth of cut as the process parameters under dry environment. Results show that the artificial neural network (ANN) compared with RSM is a better reliable and accurate approach for predicting and detecting the non-linearity of surface roughness and cutting force mathematical models in terms of correlation and errors. Indeed, the ANN prediction model provides a maximal benefit in terms of precision of 10.1% for cutting force (Fv) and 24.38% for surface roughness (Ra) compared with the RSM prediction model.

Keywords

surface roughness, cutting force, response surface methodology, artificial neural network, non linear modeling

[1] Mechanics and Structures Research Laboratory (LMS), May 8th 1945 University, BP 41030 Box 401, Guelma 24000, Algeria

[2] Laboratoire Vibrations Acoustique, INSA-Lyon, 25 bis avenue Jean Capelle, F-69621 Villeurbanne Cedex, France

[3] Université de Tunis El Manar, Ecole Nationale d'Ingénieurs de Tunis (ENIT), 1002, Tunis, Tunisie

[*] Corresponding author, e-mail: tebassihamid@yahoo.fr

1 Introduction

The Inconel 718 is one of the most important materials used in modern industries. In addition of the best properties in terms of high strength, corrosion resistance, heat resistance and fatigue resistance, the Inconel 718 has, also a low thermal conductivity as it is mentioned by Lynch [1]. Certainly, this type of alloy is difficult to machine for the following reasons as it is presented by Alauddin [2]: High work hardening rates at machining, strain rates leading to high cutting forces; abrasiveness; toughness, gummy and strong tendency to weld to the tool with forming the built-up edge; low thermal properties leading to high cutting temperatures. However, it has a wide variety of applications such as aircraft gas turbines stack gas reheaters, reciprocating engines and others.

In order to respond to the requirements of those applications, it is very important to forecasting surface roughness and cutting force. Consequently, it is necessary to search the best modeling approach of these output parameters. To obtain this objective, several approaches can be used as well as response surface methodology (RSM) and artificial neural network (ANN). Response surface methodology (RSM) is considered as a quick and useful procedure for the investigation and optimization of complex processes as well as modeling machining output parameters. Certainly, Davoodi and Eskandari [3] found that response surface methodology represents a better approach to predict tool life and productivity when turning of N-155 iron–nickel-base superalloy. Shihab et al. [4], investigated cutting temperature during hard turning of AISI 52100 alloy steel using multilayer coated carbide insert; they concluded that the developed RSM model is able to predict cutting temperature for different combination of input parameters very close to experimental values. Arokiadass et al. [5], used response surface methodology to modeling tool flank wear when end milling of LM 25 Al/SiCp with carbide tool. They concluded that the developed relationship can be effectively used to predict flank wear of carbide tool at a confidence level of 95%. Sahoo et al. [6], confirmed this conclusion when studying the development of flank wear model in turning hardened EN 24 steel with PVD TiN coated mixed ceramic insert under dry environment.

Moreover, Because of its structured nature, RSM is useful in getting insight information (e.g. interactions between different components) of the system as it is shown by Desai et al. [7].

In the last two decades, artificial neural network ANN has come up as one of the most efficient methods for empirical modeling, especially for non-linear systems as well as modeling of output parameters in machining areas. Absolutely, Das et al. [8], justified the use of artificial neural network to develop relationship between cutting process parameters and surface roughness when machining of Al-4.5Cu-1.5TiC Metal Matrix Composites, by its capability to detect non-linear relationships. Moreover, Palavar et al. [9], concluded that the prediction of aging effects on the wear behavior of Inconel 706 superalloy using ANN, can provide effective results and that the method can be effectively used to determine weight loss values in the determined parameters with a high coefficient of determination value. In addition, the ANN approach can save time in experimental processes and reduce costs as it provides quicker results.

Several research discuses the accuracy and capability of response surface methodology and artificial neural network approaches in the status of comparative study. Definitely, in their investigation to evaluate machining parameters of hot turning of stainless steel (Type 316), Ranganathan et al. [10], concluded that the ANN and RSM models are robust and accurate to estimate the surface roughness of the workpiece when hot turning of this steel. Besides, the investigation conducted by Bachy and Franke [11], for developing mathematical models by using artificial neural network (ANN) and response surface methodology (RSM), intended for the investigation of the effect of laser direct structuring (LDS) parameters on the groove dimensions, lap dimensions and the heat effective zone in the MID products. Results showed that the ANN model provides lower percentage error, which justify the author's conclusion concerning the ANN high accuracy model for predicating than the RSM model. Bingöl et al. [12], agreed root mean square error (RMSE), coefficient of determination (R^2) and absolute average deviation (AAD) as criteria of comparison between RSM and ANN for the evaluation of heavy metal biosorption process. A batch sorption process was performed using *Nigella sativa* seeds (black cumin), a novel and natural biosorbent, to remove lead ions from aqueous solution with the process variables: pH, biosorbent mass and temperature. They concluded that the ANN model was found to have a higher predictive capability than the RSM model. Maran et al. [13], proposed another criterion for comparing RSM and ANN to predict the mass transfer parameters of osmotic dehydration of papaya, this comparison is conducted in terms of root mean square error (RMSE), mean absolute error (MAE), standard error of prediction (SEP), model predictive error (MPE), chi square statistic (χ^2), and coefficient of determination (R^2) based on the validation data set. The results showed that the adequate trained ANN model is found to have higher predictive capability and more accurate in predicting as compared to RSM model. Whereas, other researchers found that RSM is better than the ANN approach in several investigations and studies. Truly, after predicting tensile strength of friction stir welded AA7039 aluminum alloy joints, Lakshminarayanan and Balasubramanian [14], concluded that RSM has a main advantage compared with ANN, this advantage consist of its ability to quantify the factor contributions from the coefficients in the regression model, identifying the insignificant main factors and interaction factors or insignificant terms in the model. Moreover, in their comparison between ANN and RSM approaches for modeling surface roughness when turning of Al7075/10/SiCp and Al 7075 hybrid composites, Kumar and Chauhan [15], concluded that the ANN prediction model produced a greater parentage error than the RSM prediction model with (R^2) values of 0.99571 and 0.9972 respectively.

In this study, a 3 level and 4 factor Box-Behenken (BBD) response surface design (RSM) and artificial neural network (ANN) based models was developed to predict the relationship between the experimental variables (cutting speed, feed rate and depth of cut) on surface roughness and cutting force. The RSM and ANN approaches are compared in terms of the coefficient of determination (R^2), root mean square error (RMSE) and model predicted error (MPE). The predicted conversion using ANN and RSM models is discussed to determine which approach has better accuracy and capability for predicting surface roughness and cutting force when turning of Inconel 718 with coated carbide tool.

2 Materials and methods

2.1 Material and experimental procedure

The aim of the current experimental work is to compare the response surface methodology (RSM) and artificial neural network (ANN) accuracy, and determine whether approach provides a superiority, capability and obvious improvement in surface roughness and cutting force models in terms of better coefficient of determination (R^2), lower root mean square error (RMSE) and model predictive error (MPE). In order to reach this objective, cutting speed, feed rate and depth of cut are chosen as process parameters. The workpiece material used in this study was Inconel 718 having a hardness of 35 HRC and the chemical composition as shown in Table 1.

Table 1 Chemical composition of workpiece

Element	C	Co	Mn	Fe	Sn	Mo	P	Ti
Quantity %	0.08	1	0.35	12.29	0.35	3.3	0.015	1.15
Element	S	Cu	Ni + Co		Al	Cr	Cb+Ta	
Quantity %	0.015	0.15	55		0.8	21	5.5	

The workpiece geometry is a cylindrical bar specimen with the diameter of 70 mm, length of 350 mm and cutting length of 20 mm. Straight turning operations have been achieved using a 6.6 kW spindle power TOS TRENCIN model SN40C lathe during dry conditions. The experimental setup is shown in Fig. 1.

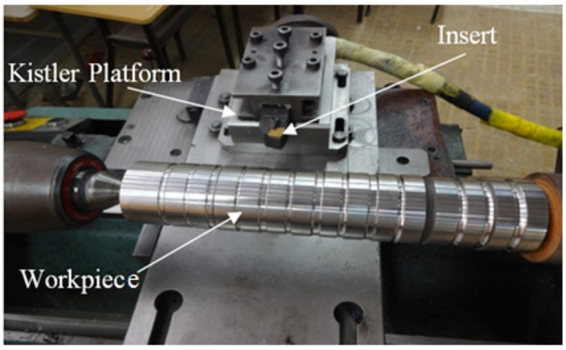

Fig. 1 Set-up and design of experiments

Cutting inserts were coated carbide as used with Settineri and Lerga [16] and Jawaid et al. [17] with the standard designation (ISO) of SNGN 120408 with radius nose of 0.8 mm, commercialized by Sandvik under GC1025. The tool holder used in this experimental study has the standard designation of CSBNR2525M12 with the following angles: $\chi r = 45°$, $\alpha = 6°$, $\gamma = -6°$ and $\lambda = -6°$ as mentioned in Coromant [18]. Surface roughness measurements have been obtained directly on the machine-tool without disassembling the workpiece, using a roughness meter (Surftest 301 Mitutoyo). The tool holder was mounted on a three-component piezoelectric dynamometer (Kistler 9257B). The measurement chain includes a charge amplifier (Kistler 5019B130), data acquisition hardware (A/D 2855A3) and graphical programming environment (DYNOWARE 2825A1-1) for data analysis and visualization.

2.2 Methods

2.2.1 Response surface methodology approach

Response surface methodology is an empirical and widely accepted statistical modeling technique employed for multiple regression analysis using quantitative data obtained from properly designed experiments to solve multivariate equations simultaneously as found by Maran et al. [19] and Tebassi et al. [20]. RSM approach proceeds with carrying out statistically designed experiments, followed by evaluating the coefficients in a mathematical relationship, the prediction of response and examining the sufficiency of the model. In this approach, the quantitative pattern of relationship between desired response and independent input variables (machining process parameters) can be interpreted equally. RSM can represent the direct and interactive effects of process parameters through the analysis of variance (ANOVA). Moreover, this approach applied in the present work is considered as a procedure to identify a relationship between independent input process parameters and output data (process response), which includes commonly six steps as it is indicated by Gaitonde et al. [21] and Tebassi et al. [20]: (1) define the independent input variables and the desired output responses, (2) adopt an experimental design plan, (3) perform regression analysis with the required model of RSM as found by Hessainia et al. [22] and Zahia et al. [23] as shown in Eq. (1).

$$\Omega = \tilde{\omega}\left(v_c, a_p, f, r, \ldots\right) + \varepsilon. \tag{1}$$

Where Ω, presents the desired response and $\tilde{\omega}$ denotes the response function. In the procedure of analysis, the approximation of Ω was proposed using the fitted second-order polynomial regression model which is called the full quadratic model. The fellow step (4) is to perform a statistical analysis of variance (ANOVA) of the independent input variables in order to find parameters which affect the response, (5) determine the situation of the RSM model and decide whether this model needs screening variables or not. A Box-Behnken Design (BBD) with three factors at three levels and three centered points was used to design the experiments as exhibited in Table 2.

Table 2 Assignment for the levels to the factors

Level	Cutting speed Vc (m/min)	Feed rate (mm/rev)	Depth of cut ap (mm)
-1	30	0.08	0.15
0	60	0.12	0.3
1	90	0.16	0.45

The process parameters selected for the experimentation were cutting speed, feed rate and depth of cut. The number of experiments N required for the development of BBD is defined by Maran et al. [24] as:

$$N = 2\,k\left(k - 1\right) + Cp. \tag{2}$$

Where k is number of factors and Cp is the number of central points. The design included three factors and three central points. Consequently, we have 15 runs. A full quadratic model was used to fit the experimental data and identify the relevant model terms using statistical software (Design Expert 9 and JMP Pro 10 software). As it is indicated by Hessainia et al. [22] and Zahia et al. [23], a quadratic model, which also includes the linear model, can be described as:

$$\tilde{\omega} = \beta_0 + \sum_{i=1}^{k} \beta_i X_i + \sum_{i=1}^{k} \beta_{ii} X_i^2 + \sum_{i<j}^{k} \beta_{ij} X_i X_j + \varepsilon_{ij} \quad \text{for } i < j. \tag{3}$$

Where $\tilde{\omega}$ denotes the predicted response , β_0 is constant, β_i, β_{ii} and β_{ij} are the coefficients of linear, quadratic and cross product terms, respectively. X_i and X_j reveal the coded variables that correspond to the studied machining parameters. The surface roughness criterion Ra and cutting force Fv are indicated as $\tilde{\omega}_1$ and $\tilde{\omega}_2$ respectively, and analyzed as responses.

In this study, the number of independent parameters (machining process parameters) is k = 3; and ε_{ij} is the error which describes the differentiation between predicted and actual values. The experimental data were analyzed, and ANOVA tables were generated. The significance of input parameters (cutting speed, feed rate and depth of cut) was evaluated by analysis of variance (ANOVA) for each response which includes F-value, Pvalu-test and Lack of Fit F-value which evaluates the significance relative to the pure error and the model adequacies were checked in terms of the values of R^2, adjusted-R^2, root mean square error (RMSE) and model predictive error (MPE).

2.2.2 Artificial neural network approach

Artificial neural network is potentially more accurate and can be used as an alternative to the polynomial regression based modeling tool, which provides the modeling of complex nonlinear relationships as it is concluded by Nagata and Chu [25], Ramezani and Afsari [26] and Sarkar et al. [27].

Two different ANN was used in this study, one for Ra and one for Fv, with a different number of hidden neurons for each. The number of neurons in the input layer is fixed as three neurons (cutting speed, feed rate and depth of cut) and the number of neurons in the output layer is fixed as one which represents the single response Ra or Fv. A neuron (node) is defined as a single computational processor, which operates with summing junction and transfer function. Moreover, according to Hagan et al. [28] and Demuth et al. [29], the relations consist of weights w and biases b with neurons addressing information.

The first phase for the training of a neural network is to design its topology. This developed topology was designated as 3-H-1, which describes three input neurons representing the chosen machining process variables (cutting speed, feed rate and depth of cut); H represents the number of neurons in a single hidden layer and one output neuron representing the chosen output machining process (surface roughness Ra or cutting forces Fv). The optimal neural network architecture was chosen between all architectures according to two steps.

First step: Choose of the optimal neural network architecture is done according to Dey and Chakraborty [30] in terms of better coefficient of determination and lower root mean square error (RMSE) with varying the number of neurons in the single hidden layer. Consequently, in this step, the number of neurons in the single hidden layer H was known.

Second step: The optimal neural network architecture obtained in the precedent step was examined in terms of higher coefficient of determination (R^2) and lower root mean square error (RMSE) with varying the number of iterations. The experimental data were divided into a training (10 tests) and validation (5tests) with a leaning rate value of (0.01). The activation function used in this study is a hyperbolic tangent which is a sigmoid function. According to Sall et al. [31], the hyperbolic tangent (TanH) transforms values to be between -1 and 1; its formula is given in Eq. (4), where x is a linear combination of the X variables.

$$TanH = \frac{e^{2x}-1}{e^{2x}+1}. \tag{4}$$

2.2.3 Comparison approach between RSM and ANN models

In order to evaluate the goodness of fitting and prediction accuracy of the constructed models, coefficients of determination (R^2), performance function error analyses of root mean square error (RMSE) and model predictive error (MPE) were carried out between experimental and predicted data for surface roughness and cutting force as shown in the research of Ramezani [32]. The coefficient of determination (R^2), root mean square error (RMSE) and model predictive error (MPE) are calculated as cited by Rajendra et al. [33] and García-Gimeno et al. [34] as shown in Eq. (5), Eq. (6) and Eq. (7), respectively:

$$R^2 = \frac{\sum_{i=1}^{n}\left(y_{i,p}-y_{i,e}\right)}{\sum_{i=1}^{n}\left(y_{i,p}-y_{average}\right)^2}. \tag{5}$$

$$RMSE = \frac{\sqrt{\sum_{i=1}^{n}\left(y_{i,e}-y_{i,p}\right)^2}}{n}. \tag{6}$$

$$MPE(\%) = \frac{100}{n}\sum_{i=1}^{n}\left|\frac{\left(y_{i,e}-y_{i,p}\right)}{y_{i,p}}\right|. \tag{7}$$

When, n is the number of experiments; $y_{i,e}$ is the experimental value of the i^{th} experiment; $y_{i,p}$ is the predicted value of the i^{th} experiment which calculated by the model; and $y_{average}$ is the average value of experimentally determined values. In order to study and compare RSM and ANN models and determine which model can sufficiently and accurately predict surface roughness and cutting forces and according to Sahoo et al. [35], values predicted by the RSM and ANN models are plotted against the corresponding actual values for showing their ability truthfulness.

3 Results and discussion

3.1 RSM modelling

Table 3 shows the experimental results of surface roughness (Ra) and cutting force (Fv). A statistical analysis was performed with the objective of analyzing the influence of cutting speed, feed rate and depth of cut on the obtained outputs, which out for a 5% significance level, i.e., for a 95% confidence level.

Table 3 Experimental results for surface roughness and cutting force

Run	Vc (m/min)	ap (mm)	f (mm/rev)	Ra (µm)	Fv (N)
1	90	0.45	0.12	1.19	89.27
2	90	0.3	0.08	1.2	52.92
3	60	0.3	0.12	1.51	56.17
4	60	0.3	0.12	1.22	59.33
5	60	0.3	0.12	1.18	56.17
6	90	0.3	0.16	1.57	52.55
7	30	0.45	0.12	0.8	101.22
8	30	0.3	0.16	1.5	70.1
9	30	0.15	0.12	0.54	62.75
10	60	0.45	0.08	0.47	80.34
11	90	0.15	0.12	1.41	24.88
12	60	0.15	0.08	0.58	22.25
13	60	0.45	0.16	1.86	91.24
14	30	0.3	0.08	0.46	56.06
15	60	0.15	0,16	0.88	26.91

3.1.1 Surface roughness

Table 4 shows the results of ANOVA corresponding to Ra. According to this table, the model F-value of 7.77 implies the model is significant. There is only a 1.81% chance that an F-value this large could occur due to noise. Values of "Prob > F" less than 0.05 indicate model terms are significant, in this case Vc, f, Vc*f and ap^2 are all significant model terms. Values greater than 0.1 indicate the model terms are not significant. The "Lack of Fit F-value" of 1.25 implies the Lack of Fit is not significant relative to the pure error. There is a 47.42% chance that a "Lack of Fit F-value" this large could occur due to noise.

Table 4 Analysis of variance for Ra

Source	Sum of Squares	df	Mean Square	F Value	p-value Prob > F
Model	2.60328167	9	0.2892535	7.7718020	0.01806635
A-Vc	0.535612	1	0.5356125	14.391093	0.01271199
B-ap	0.103512	1	0.1035125	2.7812234	0.15624955
C-f	1.20125	1	1.20125	32.275760	0.0023537
AB	0.0576	1	0.0576	1.5476243	0.26862586
AC	0.112225	1	0.112225	3.0153150	0.14299472
BC	0.297025	1	0.297025	7.9806099	0.03689108
A^2	0.00641026	1	0.0064102	0.1722338	0.69534095
B^2	0.28262561	1	0.2826256	7.5937210	0.04003978
C^2	0.02314106	1	0.0231410	0.6217641	0.46611624
Residual	0.18609167	5	0.0372183		
Lack of Fit	0.121225	3	0.0404083	1.245889	0.47422745
Pure Error	0.06486667	2	0.0324333		
Cor Total	2.78937333	14			

The perturbation plot in Fig. 2 helps to compare the effect of all the factors at a particular point in the design space on surface roughness. A steep slope for Vc and f shows that the response is sensitive to those factors. Indeed, from Fig. 3 that shows the contribution percent of the factors on the response Ra, it can be seen that the most significant factor on Ra is the feed rate f, which explains, 45 % contribution of the total variation.

The next largest contribution on Ra comes from the cutting speed Vc with the contribution of 20 %. Deph of cut ap have lower contribution value (4 %).

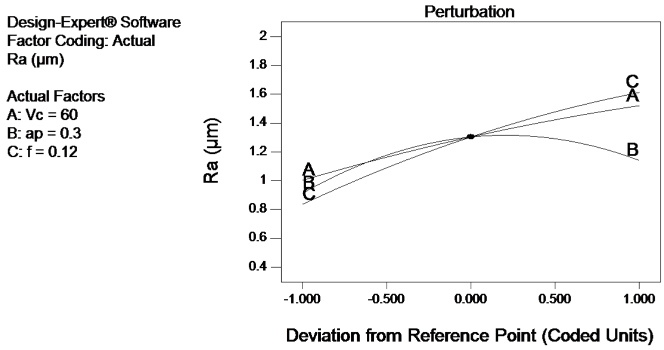

Fig. 2 Perturbation plot for Ra

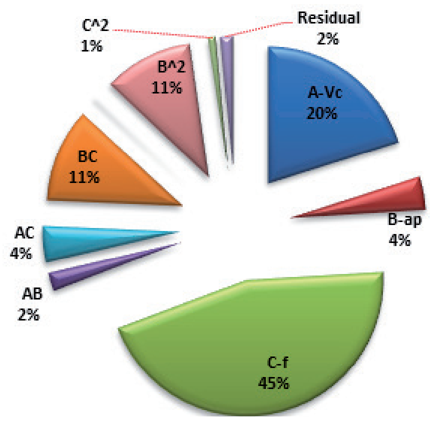

Fig. 3 Terms contribution (%) on Ra

When the data are analyzed, the following response function second order equation for Ra, is obtained in terms of actual factors as:

$$\begin{aligned} Ra = 1.30 + 0.26Vc + 0.11ap + 0.39f \\ -0.12Vc*ap - 0.17Vc*f + 0.27ap*f \\ -0.042*Vc^2 - 0.28*ap^2 - 0.079*f^2 \end{aligned} \tag{8}$$

This equation can be used to make predictions about the response for given levels of each factor, and its accuracy can be evaluated. Certainly, R^2 has a value of 0.9333 and adjusted-R^2 of 0.8132. The Adeq Precision of 8.586 measures the signal to noise ratio. A ratio greater than 4 is desirable [36]. Consequently, a ratio of 8.586 indicates an adequate signal. This model can be used to navigate the design space. Root mean square error (RMSE) and model predictive error (MPE) are calculated, and their values are: 0.1929 and 10.6549 % respectively.

3.1.2 Cutting force

According to Table 5, that shows analysis of variance (ANOVA) for Fv. The model F-value of 46.87 implies the model is significant. There is only a 0.03% chance that an F-value this large could occur due to noise. Values of "Prob > F" less than 0.05 indicate model terms are significant. In this case Vc, ap, f, Vc^2 are significant model terms. Values greater than 0.1 indicate the model terms are not significant. The "Lack of Fit F-value" of 55.82 implies the Lack of Fit is significant. There is only a 1.77% chance that a "Lack of Fit F-value" this large could occur due to noise.

Table 5 Analysis of variance for Fv

Source	Sum of Squares	df	Mean Square	F Value	p-value Prob > F
Model	33973.25	9	3774.81	46.87	0.0003
A-Vc	1921.07	1	1921.07	23.85	0.0045
B-ap	22717.53	1	22717.53	282.10	< 0.0001
C-f	8069.58	1	8069.58	100.20	0.0002
AB	222.01	1	222.01	2.76	0.1577
AC	23.57	1	23.57	0.29	0.6117
BC	301.89	1	301.89	3.75	0.1106
A^2	654.85	1	654.85	8.13	0.0358
B^2	90.75	1	90.75	1.13	0.3370
C^2	0.049	1	0.049	6.064E-004	0.9813
Residual	402.66	5	80.53		
Lack of Fit	397.90	3	132.63	55.82	0.0177
Pure Error	0.064866	2	0.03243		
Cor Total	34375.90	14			

The perturbation plot in Fig. 4 for Fv helps to compare the effect of all the factors at a particular point in the design space. A steep slope for ap and f shows that the response is sensitive to those factors.

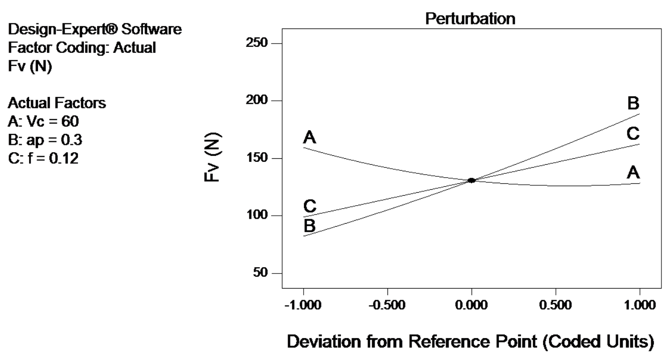

Fig. 4 Perturbation plot for Fv

Indeed, from Fig. 5 that shows the contribution percent of the factors on Fv, it can be seen that the most significant factor is the depth of cut ap, which explains 66 % contribution of the total variation. The next largest contribution on Fv comes from the feed rate f with the contributions of 23 %. Cutting speed has a lower contribution value of contribution ratio (6 %). The second-order polynomial equation of cutting force Fv is obtained in terms of actual factors as shown in Eq. (9)

$$\begin{aligned} Fv = {} & 130.4 - 3.03163Vc - 50.025ap + 221.00f \\ & +1.65556Vc*ap + 2.02292Vc*f + 1447.91667ap*f \\ & +0.014797*Vc^2 + 220.33333*ap^2 + 71.875*f^2 \end{aligned} \tag{9}$$

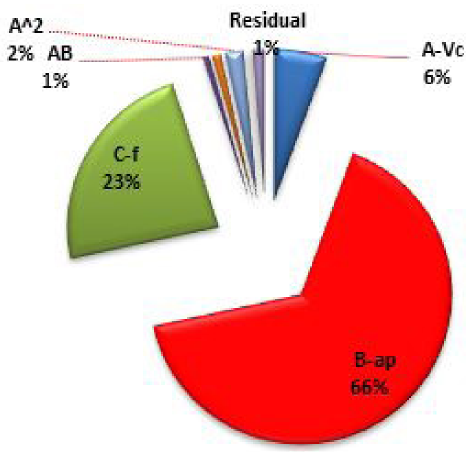

Fig. 5 Terms contribution (%) on Fv

Model accuracy can be evaluated. Surely, R^2 is to 0.9883 and adjusted-$R^2$of 0.9672. The Adeq Precision of 23.215 measures the signal to noise ratio [36]. A ratio greater than 4 is desirable. Consequently, a ratio of 23.215 indicates an adequate signal. This model can be used to navigate the design space. Root mean square error (RMSE) and model predictive error (MPE) are calculated, and their values are: 8.9739 and 3.5398 % respectively.

3.2 ANN modelling

3.2.1 Surface roughness

The first step of ANN modeling was to optimize a neural network with the aim of obtaining an ANN model with a minimal dimension and minimal errors in both training and validation by using the leaning rate of 0.01. Indeed, this step consists in choosing the optimal number of neurons in the single hidden layer H in terms of better coefficient of determination (R^2) and lower root mean square error (RMSE).

Figure 6 shows that the optimal number of neurons is 4, which, explain 0.963805 for training R^2 and 0.99999 for validation R^2 with the training root mean square error (RMSE) of 0.073585 and 0.001520 for validation as shown in Fig. 7. Consequently, the optimal architecture is 3-4-1 as shown in Fig. 8.

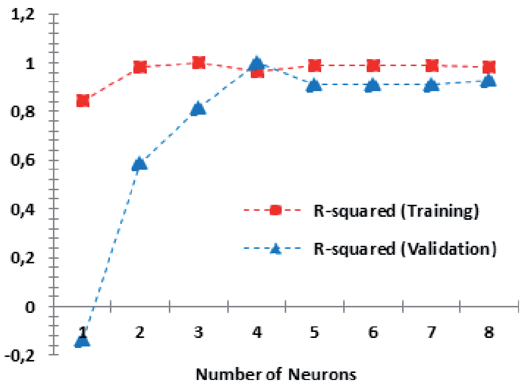

Fig. 6 Coefficient of determination versus the number of neurons in the single hidden layer for Ra

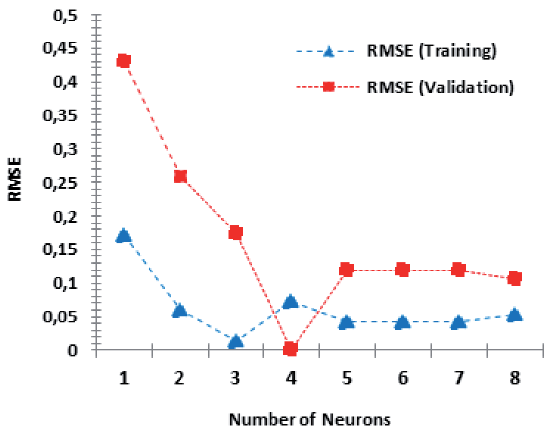

Fig. 7 Root mean square error versus the number of neurons in the single hidden layer for Ra

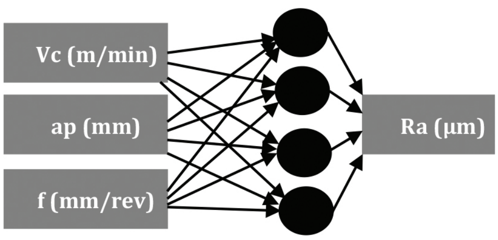

Fig. 8 Optimal architecture 3-4-1 for modeling Ra

The second step consists in obtaining the optimal number of iterations according to this architecture (3-4-1) in terms of better coefficient of determination (R^2) and lower root mean square error (RMSE). Truly, Fig. 9 shows the variation of the coefficient of determination (R^2) versus the number of iterations for both training and validation. It can be seen from this figure that the number of iterations of 450 is considered as optimal, because it can generate the R^2 of 0.98926 for training and 0.93399 for validation. Likewise, this number of iteration results a training root mean square error (RMSE) of 0.04081 and 0.12261 for validation as shown in Fig. 10. Also, for the 3-4-1 architecture, with the number of iterations of 450 for training, the model predictive error (MPE) calculated according to Eq. (7), is 2.37788 %.

3.2.2 Cutting force

The first step consists in the choosing of the optimal number of neurons in the single hidden layer H in terms of better coefficient of determination and lower root mean square error (RMSE) using the leaning rate of 0.01. Figure 11 shows that the optimal number of neurons is 8, which explain 0.99988 for training R^2 and 0.99888 for validation R^2. In addition, this architecture can generate the root mean square error (RMSE) of 0.5578 for training and 0.76499 for validation as shown in Fig. 12. Consequently, the optimal architecture is 3-8-1 as shown in Fig. 13.

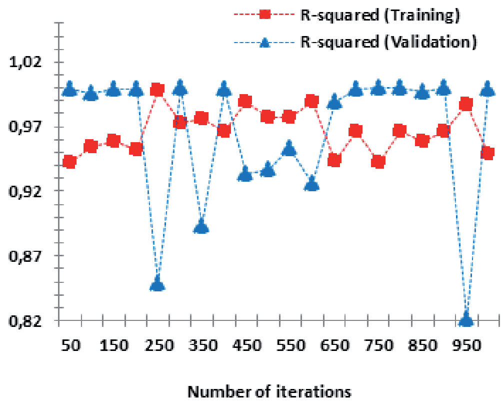

Fig. 9 Coefficient of determination versus the number of iterations using 3-4-1 architecture for Ra

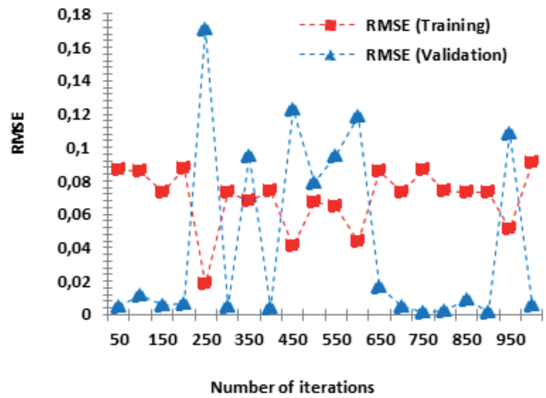

Fig. 10 Root mean square error versus the number of iterations using 3-4-1 architecture for Ra

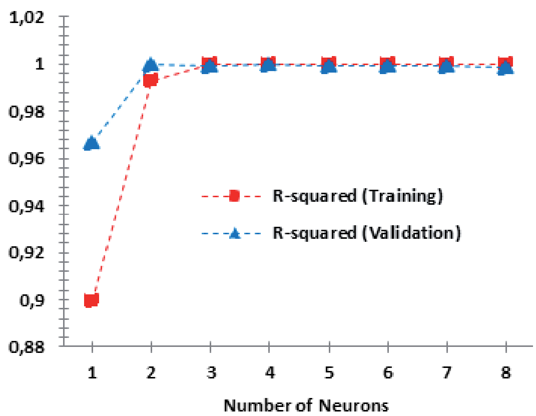

Fig. 11 Coefficient of determination versus the number of neurons in the single hidden layer for Fv

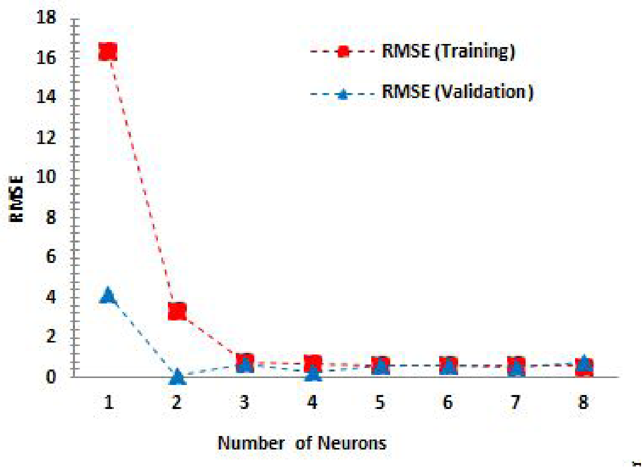

Fig. 12 Root mean square error versus the number of neurons in the single hidden layer for Fv

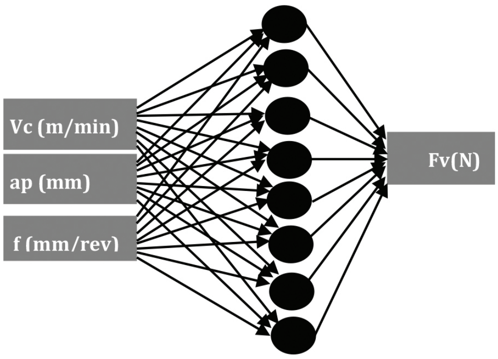

Fig. 13 Optimal architecture 3-8-1 for modeling Fv

The second step consists in obtaining the optimal number of iterations according to this architecture (3-8-1) in terms of better coefficient of determination (R^2) and lower root mean square error (RMSE).

Figure 14 shows the variation of the coefficient of determination versus the number of iterations for both training and validation according to the optimal architecture (3-8-1). It can be seen from this figure that the number of iterations of 150 is considered as optimal, because it can generate the R^2 of 0.99979 for training and 1 for validation. Likewise, this number of iteration results a training root mean square error (RMSE) of 0.63012 and 0.00973 for validation as shown in Fig. 15. Also, for the 3-8-1 architecture, the model predictive error (MPE) is 0.19985 %. This value is obtained after 150 iterations.

3.3 Comparison of RSM and ANN models

The question is: which approximation model is more trustable offering better accuracy in fitting experimental data and giving a better optimal solution confirmed by experiment? Moreover, it is important to reveal the advantages of each methodology and differences between them. At this stage, comparison criteria are needed to quantify the difference between values produced by both models and the actual values. In order to test the accuracy of both the ANN and RSM models. The performances of constructed ANN and RSM models were measured in terms of better coefficient of determination (R^2), root mean square error (RMSE) and model predictive error (MPE) for surface roughness and cutting force. The diagram that compares the experimental data versus the predicted RSM and ANN values for Ra is shown in Fig. 16. It is observed that the deviations of the predicted and experimental data are smaller for ANN model compared with RSM model.

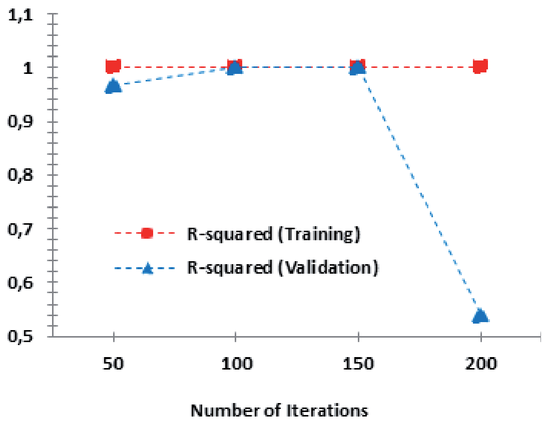

Fig. 14 Coefficient of determination versus the number of iterations using 3-8-1 architecture for Fv

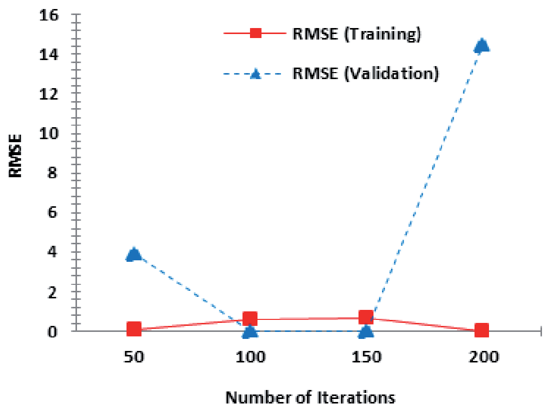

Fig. 15 Root mean square error versus the number of iterations using 3-8-1 architecture for Fv

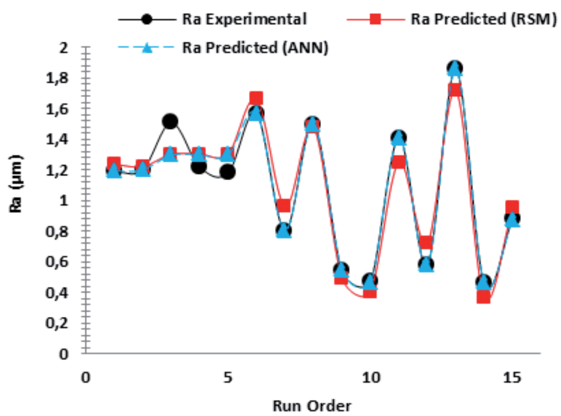

Fig. 16 Comparison between experimental and predicted Ra with RSM and ANN models

Certainly, the obtained R^2 for the surface roughness RSM model is to 0.9333 and its value for ANN model is to 0.98926. This can clarify the capability of ANN model, as shown in Fig. 17, which illustrates, the lower residuals in Ra for ANN model compared with RSM model. In addition, RMSE and MPE values are 0.1929 and 10.6549 % for the surface roughness RSM model. Their values for the surface roughness ANN model are 0.04081 and 2.37788 % respectively.

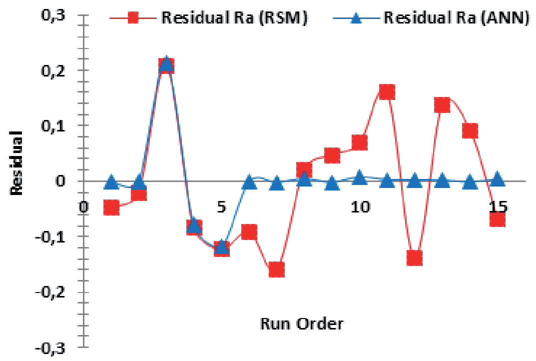

Fig. 17 Comparison between RSM and ANN models residuals for Ra

Relating to cutting force Fv, the diagram that compares the experimental data versus the predicted RSM and ANN values is shown in Fig. 18. Certainly, the obtained R^2 values for the cutting force RSM model and ANN model are: 0.9883 and 0.9997 respectively. This can clarify the competence of ANN model, as shown in Fig. 19, which illustrates, the lower residuals in Fv for ANN model compared with RSM model.

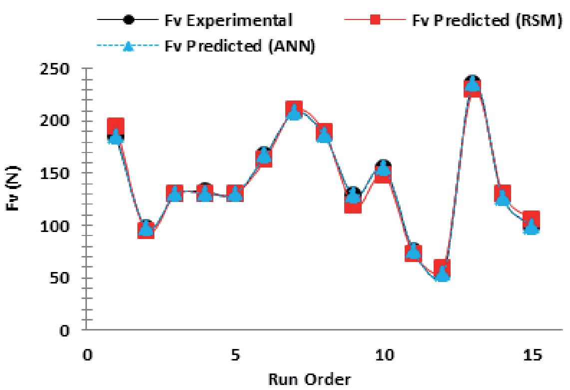

Fig. 18 Comparison between experimental and predicted Fv with RSM and ANN models

In addition, ANN model presents a good root mean square error (RMSE) and model predictive error (MPE) compared with RSM model. Really, RMSE and MPE values are 8.9739 and 3.53985 % for cutting force RSM model. Their values for cutting force ANN model are 0.63012 and 0.19985 % respectively. Moreover, ANN prediction model offered a maximal benefit in precision of 10.1% for cutting force Fv and 24.38% for surface roughness Ra compared with RSM prediction model as shown in Fig. 20.

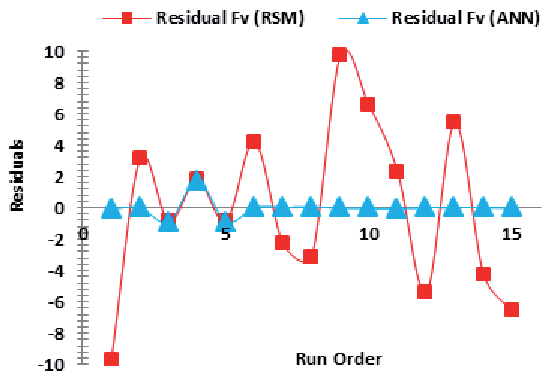

Fig. 19 Comparison between RSM and ANN models residuals for Fv

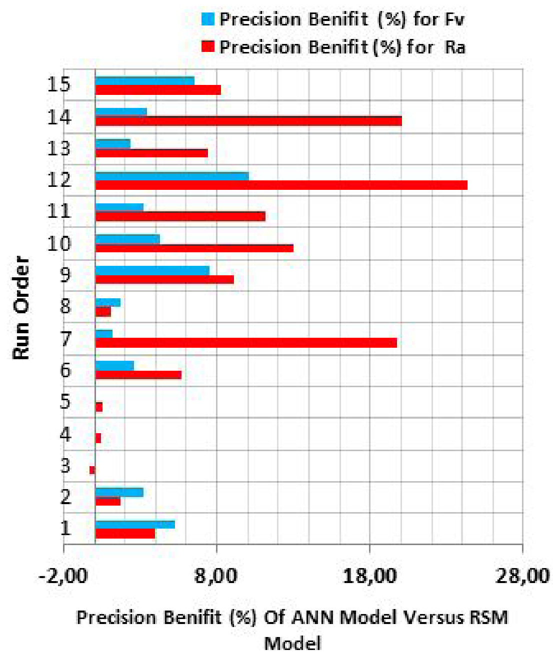

Fig. 20 Benefit in terms of precision percent offered by ANN model compared with RSM model for surface roughness Ra and cutting force Fv

4 Conclusion

This study compares the performance of surface response (RSM) and neural network (ANN) methodologies with their modeling, prediction and generalization capabilities using the experimental data based on the Box-Behnken design for surface roughness and cutting force. The following conclusions are drawn from this work:

From analysis of variance (ANOVA) it can be concluded that the surface roughness is significantly affected by feed rate and cutting speed with the contribution of 45% and 20% respectively. The cutting force Fv is significantly affected by depth of cut, feed rate and cutting speed with the contribution of 66%, 23% and 6% respectively.

From the comparative study, ANN models are found to be capable for better predictions of surface roughness and cutting force within the range they trained than the RSM models in terms of better correlation and lower error. Indeed, the RSM prediction model for Ra presents a coefficient of determination (R^2), root mean square error (RMSE) and the model predictive error (MPE) of 0.9333, 0.1929 and 10.6549%, respectively, compared with their values obtained with ANN prediction model of 0.98926, 0.04081 and 2.37788% respectively.

In addition, the RSM prediction model for Fv presents a coefficient of determination (R^2), root mean square error (RMSE) and the model predictive error (MPE) of 0.9883, 8.9739 and 3.5398% respectively, their values obtained with ANN model are 0.99979, 0.63012 and 0.19985% respectively. Moreover, the ANN prediction model provides a maximal benefit in terms of precision of 10.1% for Fv and 24.38% for Ra compared with the RSM prediction model.

The approaches used in the present work proved their efficiency in investigating and modeling the machining output parameters, such as: surface roughness and cutting force. Therefore, the results of this research could be very helpful for scientific researchers as well as for mechanical manufacturing companies.

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