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Modeling Blanking Process Using Multiple Regression Analysis and Artificial Neural Networks

Emad S. Al-Momani, Ahmad T. Mayyas, Ibrahim Rawabdeh, and Rajaa Alqudah

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The design of blanking processes requires the availability of a procedure able to deal with both tooling and mechanical properties of the workpiece material (blank thickness, hardness, ductility, etc.). This research presents the development and comparison of two models to predict the quality of the blanked edge represented by burrs height, the first model is an artificial neural network (ANN) based, while the second model is a multiple regression analysis (MRA) based. Finite Element modeling of the blanking process was used to generate the data for both models. Both ANN and MRA are able to give good prediction results, however, ANN still more accurate because it deals efficiently with hidden nonlinear relations when compared to MRA. The comparison between experimental and model results shows that average absolute relative error in the case of ANN was <2.20% for carbon steel and 4.85% for corrosion-resistant steel (CRES) compared to 15.18% for carbon steel and 14.22% for CRES obtained from the second order MRA. Therefore, by using ANN outputs, satisfactory results can be estimated rather than measured and hence reduce testing time and cost.

Keywords artificial neural networks, blanking, burrs height, regression, steel

1. Introduction

Research in the control of blanking operations is currently being performed to improve monitoring and control of components quality; other motivations include the reduction of reject volume, reduction of manual quality control, and the reduction of cost of replacing tools after catastrophic failure. Finite element analysis (FEA) modeling was widely used in the area of sheet metal forming with the development of sophisticated models of fracture and damage mechanics, researchers were able to obtain numerical tools to analyze the blanking process. However, FEA allow many aspects of the blanking process to be analyzed in detail under various conditions in a research environment. Artificial intelligence techniques like artificial neural networks (ANN), fuzzy logic, and genetic algorithms have been widely used in the recent years due to their superior prediction and optimization abilities compared to other statistical models.

Emad S. Al-Momani, Department of Systems Science and Industrial Engineering, Binghamton University, SUNY, Binghamton, NY 13902-6000, USA; **Ahmad T. Mayyas**, Department of Automotive Engineering, Clemson University, Clemson, SC 29634, USA; and International Center for Automotive Research (CU-ICAR), CGEC, Clemson University, 4 Research Drive, Greenville, SC 29607, USA; **Ibrahim Rawabdeh**, Department of Industrial Engineering, University of Jordan, Amman 11942, Jordan; and **Rajaa Alqudah**, Department of Electrical Engineering and Computer Science, Syracuse University, Syracuse, NY 13244, USA. Contact e-mails: ahmadm@g.clemson.edu and mayyas111@ gmail.com.

Sheet metal blanking is one of the main industrial processes for producing mechanical parts; therefore attention must be focused on its modeling. In this study, multiple regression analysis (MRA) and backpropagation neural network algorithm were used to predict the burrs height formation on blanked parts based on a set of input parameters. The major advantage of the neural network predictions is that the model can estimate burrs height very fast and accurately. Through the investigation, it becomes clear that the ANN method can be used either as prediction or optimization techniques, which in turn reduce the trial and experimental errors to design a sheet metal blanking process. Moreover, the proposed ANN can be used to contribute toward the development of an on-line assessment system of burrs height evolution during the blanking processes.

Using of ANN in the area of sheet metal shearing is still attractive and competitive compared to other prediction methods. For example, Wadi and Balendra (Ref 1, 2) proposed a method of neural networks (NN) to monitor product quality of blanking by assessing changes in tool geometry, material quality, and tool configuration. Hambli (Ref 3) developed a backpropagation NN model to predict the burr height based on data that was obtained through finite element modeling; the correctness of the used finite element model was verified experimentally. Hambli changed two major parameter sets; basically the tool wear state and punch-die clearance. NN was able to reproduce the training data with good accuracy, however, in this study, the effects of other parameters on burr height are investigated, these parameters include punch-die clearance, blank thickness, and blank holder force (BHF). Hambli and Guerin (Ref 4) developed a methodology to obtain the optimum punch-die clearance for a given sheet material by the simulation of the blanking process. The proposed approach combines predictive finite element and neural network modeling of the leading blanking parameters.

In this study, the numerical results of damage and fracture obtained by finite element were utilized to train the developed simulation environment based on back propagation neural network modeling. Husson et al. (Ref 5) used finite elements models using the commercial finite elements code ABAQUS to study the influence of process parameters such as punch-die clearance, tools geometry, and friction on blanking force and blank profile (sheared edge). This study focuses on the finite elements simulations of a blanking process using a new viscoplastic model for the evolution of the flow stress coupled with a new damage model. The finite elements simulation predictions have been compared with experimental results. Then, the finite elements simulations have been used to assess the influence of punch-die clearance as well as the influence of tool wear and friction on sheared edge quality.

Quality control and process monitoring in sheet metal manufacturing processes have been investigated by many researchers. Al-Momani et al. (Ref 6, 7) presented an attempt to optimize the blanking process using systematic experimental design, numerical simulation, and Monte Carlo simulation. Results show the effectiveness of combining the mentioned techniques to reduce the cost of optimizing the blanking process in addition to reducing manufacturing lead time. A robust process against variations in its conditions was obtained. Garcia (Ref 8) studied the stamping process to avoid production breakdowns and to improve the reliability of the stamping process. He used an integrated automatic control which includes a system based on the use of sensors, artificial vision, and NN for the diagnosis and the prediction of the process results. A second system based on fuzzy logic was also used for the automatic control system. In-process control principles were extensively reported by researchers for manufacturing processes outside the area of sheet metal manufacturing as well, for example turning, on-line monitoring of tool wear (Ref 9–11).

Other researches dealt with conditional based maintenance in sheet metal blanking (Ref 12–14). Some complicated stochastic models have been proposed such as hidden Markov model (Ref 15), but these models are complicated and hard to be applied to the real in-process monitoring.

2. Multiple Regression Analysis

Regression analysis is a statistical tool for the investigation of relationships between variables. Usually, the investigator seeks to ascertain the effect of one variable upon another. MRA is widely used to model the cause and effect relationship between inputs and outputs and can be generally expressed as

$$Y = f(X_1, X_2, \ldots, X_n; \theta_1, \theta_2, \ldots, \theta_n) + \varepsilon \qquad \text{(Eq 1)}$$

where Y is a dependent variable (i.e., output variable), $X_1,\ldots,X_n$ are independent or explanatory variables (i.e., input variables), $\theta_1 - \theta_p$ are regression parameters, ε is a random error, which is assumed to be normally distributed with zero mean and constant variance σ^2, and f is a known function, which may be linear or nonlinear. If f is linear, then Eq 1 becomes a multiple linear regression model which can be expressed as:

$$Y = b_0 + b_1X_1 + b_2X_2 + \cdots + b_nX_n + \varepsilon \qquad \text{(Eq 2)}$$

where b_0 is a constant and called intercept. Different functional forms decide different MRA models.

3. Artificial Neural Networks (ANN)

Artificial neural networks have highly interconnected structure similar to brain cells of human NN and consist of large number of simple processing elements called neurons, which are arranged in different layers in the network. So artificial neural network is considered a massive parallel distributed processor made up of simple processing units called neurons. This artificial intelligence model has a natural propensity for storing experimental knowledge and making it available for use. It mimics the brain in two respects:

1. The network acquires the knowledge from its environment through a learning process.
2. Interconnection weights are adjusted and used to store and recall the acquired knowledge.

Each network consists of an input layer, an output layer, and one or more hidden layers. One of the well-known advantages of ANN is its ability to learn from the sample set, which is called training set, in a supervised or unsupervised learning process. Once the architecture of network is defined, then through learning process, weights are calculated so as to present the desire output (See Fig. 1) (Ref 16–18).

Learning in ANN is an adaptive process where the network has the ability to update its parameters (mainly weights between nodes). Network parameters are changed according to predefined equations called the learning rules. The learning rules usually derived from predefined error measures. An example of an error measure in a supervised learning procedure is the squared error between the output of the model and the desired output. This requires knowledge of the desired value for a given input. In most ANN algorithms, a minimization objective function is performed using gradient descent optimization

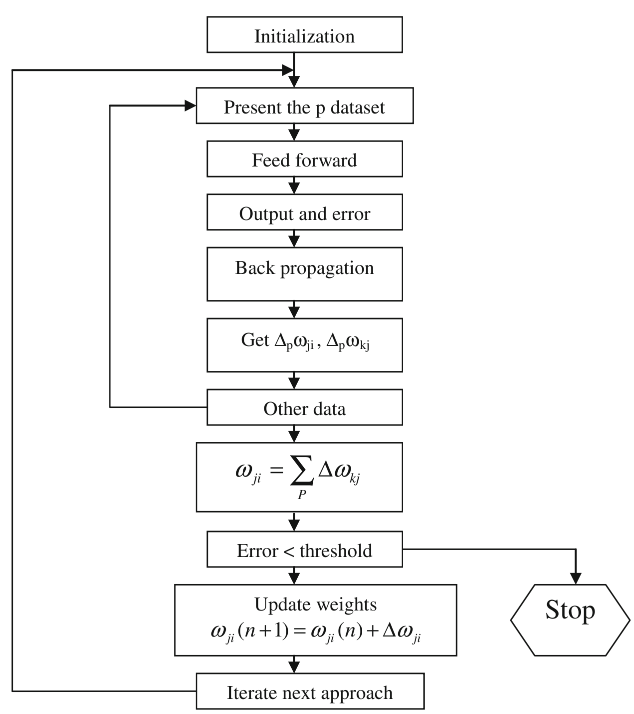

Fig. 1 Feedforward backpropagation ANN training algorithm

methods to minimize the squared error between the predicted outputs of the model and the actual outputs.

The training process must be stopped at the right time; otherwise, too long training will result in overlearning network. Overlearning means that the neural network reaches a limit where it extracts too much information from the particular training cases (examples) and loses the relevant information of the general case (overall training set).

Usually, the neural network performance is tested with a testing set which is not part of the training set. Testing can be done after completion of training process or during the training process where a testing cycle is performed upon completion of predetermined training cycles (in this study, the testing cycle was performed every 100 cycle of training cycles). By following this method, ANN will modify its weights based on the relative error it gets from the testing cycle, which in turn insure accuracy and less training time. However, the testing set can be considered as a set of examples or cases that the ANN has not seen and used primarily to check the reproducibility of the ANN in predicting output for new cases.

Cross-validation methods can also be used to avoid overlearning. In cross-validation, the ANN has the ability to switch the places of the training set and the testing set and compares the performance of the resulting networks.

4. Experimental Procedures

4.1 Background of Burrs

Burrs formation during blanking operation is one of the problems that face the blanking community. Burrs increase tools wear and reduce its life, in addition it affect the blanked part quality which may result either on a post blanking steps to remove burrs or to scrap the product. A schematic geometry of the blanking edge including burrs is shown in Fig. 2.

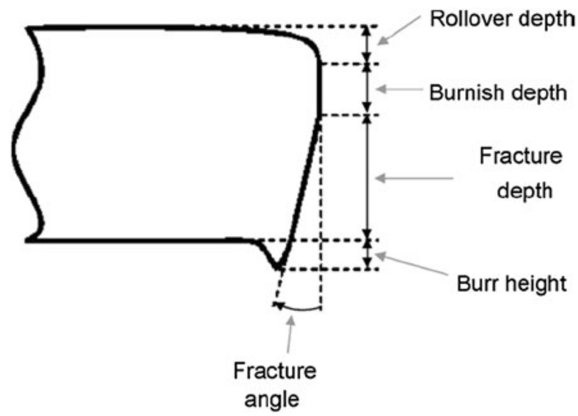

Fig. 2 Geometry of the blanked edge (Ref 5)

4.2 Materials Property Measurement

Tensile test was performed into two stages to provide information on the properties of materials under uniaxial tensile stresses. The purpose of the first stage was to get the stress-strain diagram while the purpose of the second stage was to get the modulus of elasticity and Poisson's ratio. Instron (1195) universal testing machine was used to apply tensile forces by means of a moving crosshead. The machine is equipped with a load cell that provides an output voltage proportional to the applied load and has a nominal capacity of 100 KN. An extensometer was installed to measure the elongation of the specimen which provides an output voltage that is proportional to the specimen elongation. A recording chart is used to construct a load-deformation curve. Strain indicator in addition to switch and balance unit were used in measuring the strain gage readings for getting the modulus of elasticity and Poisson's ratio. Tensile tests were conducted on dog-bone shaped samples in accordance with American Society of Testing Methods E 8M-89. The load-elongation diagram for both materials (carbon steel and CRES) is shown in Fig. 3. The modulus of elasticity (E) was obtained as the slope of a straight line represents the relationship of stress versus axial strain, while Poisson's ratio (ε) was obtained as the slope of a straight line represents the relationship of axial strain versus lateral strain. Table 1 summarizes the mechanical characteristics of the used carbon steel and corrosion-resistance steel (CRES).

4.3 Experimental Methodology

A detailed description of the experimental methodology can be found in (Ref 6, 7). Finite Element Simulation was performed as a part of this study. A simulation of an axis-symmetric blanking operation of sheet metal was performed. The simulation is designed to study the previously mentioned parameters at their corresponding levels (Table 2). Eighty simulations were performed for the above configuration according to the whole combinations of parameters. Simulations were conducted on the commercial finite element software package ABAQUS/Explicit. The process is simplified by using a two-dimensional situation, under plane-strain conditions, since in a normal blanking operation the punch-die clearance is usually very small in relation to the blank diameter, otherwise, the deformation will be in a 3-D form. In all simulations, a circular disc with a diameter of 55 mm has been used as the blank. Only half of the blank was modeled because the blanking process is symmetric about a plane along the center of the blank. In order to assess the quality of the model, a comparison with experiments is made. A company that deals with dies and tools manufacturing and steel sheets forming, is selected for conducting the experiments. For more details about the FEA and the verifications process, please return to Al-Momani and Rawabdeh (Ref 6). Figure 4 shows a schematic representation of the blanking process.

5. Results and Discussion

5.1 Multiple Regression Analysis Results

To establish the prediction model, MINITAB 15 statistical software package was used to perform the MRA using the available data. Table 2 shows the independent factors and their levels that used for developing of the MRA and ANN.

A second order regression model (full quadratic regression model) was tested to check for any important second order interactions. The second order regression models are shown in Tables 3 and 4 for carbon steel and CRES, respectively. In these models higher values of both R^2 and R^2(adj.) were obtained which indicate very good correlation.

Table 1 Some mechanical characteristics of the used carbon steel and CRES obtained from the load-elongation diagrams

Material	Yield stress, MPa	Ultimate tensile stress, MPa	Ductility as % elongation	Strain-hardening exponent	Strength coefficient, MPa	Modulus of elasticity, GPa	Poisons ratio
Carbon Steel	201	296	37.6	0.23546	524.45	201	0.31
CRES	296.54	475	24.4	0.20651	816.44	187	0.29

Table 2 Blanking process factors and their corresponding level values

		Level values				
Factor	**Number of levels**	**Level 1**	**Level 2**	**Level 3**	**Level 4**	**Level 5**
Clearance	5	5	10	15	20	25
Thickness	4	0.5	0.6	0.7	0.8	
Blank holder force	2	0	3000			

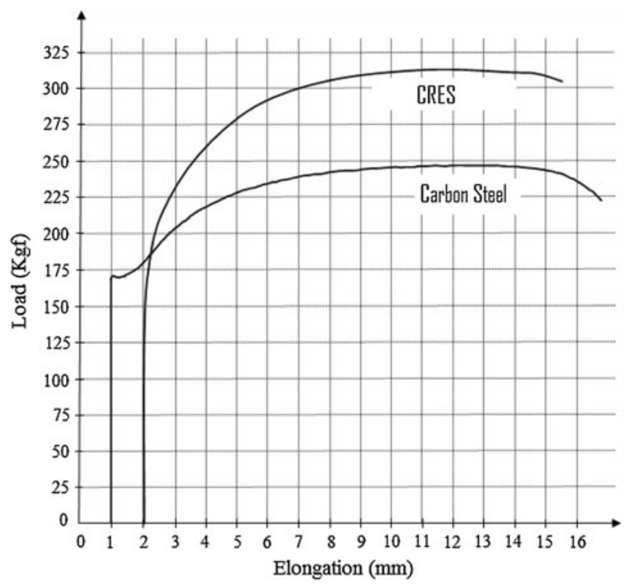

Fig. 3 Load-elongation diagram for carbon steel and CRES

Table 3 Second order regression model for carbon steel

Term	Coefficient	SE coef.	*T*	*p*
Constant	0.080216	0.038908	2.062	0.048
Clearance	0.002366	0.000983	2.408	0.022
Thickness	−0.05766	0.116916	−0.493	0.625
BHF	−0.00001	0.000004	−2.761	0.01
Clearance*clearance	0.000051	0.000021	2.43	0.021
Thickness*thickness	0.045782	0.088583	0.517	0.609
Clearance*thickness	−0.00153	0.00112	−1.361	0.183
Clearance*BHF	0.000001	0	13.68	0
Thickness*BHF	0.000004	0.000005	0.802	0.429

S = 0.00560245; PRESS = 0.00156979; R^2 = 98.34%; R^2(pred) = 97.32%; R^2(adj.) = 97.91%

In the second order regression model, the adjusted-R^2 values was close to 1.0 and the p-values were close to zero as presented in Tables 3 and 4 which indicate a goodness of fitness for this model (Ref 19). Among the three parameters considered: thickness, clearance and BHF, only clearance and BHF significantly affect the burrs height independently for a significance level $\alpha = 0.05$.

In the case of carbon steel, the final second order regression model with significant terms (significance level $\alpha = 0.05$) can be expressed as follows:

$$\text{Burr height} = 0.08022 + 0.00237X_1 - 0.00001X_3 + 0.000051X_1^2 + 0.000001X_1X_3 \quad \text{(Eq 3)}$$

where X_1 is the clearance (mm); X_2 is the thickness (mm); and X_3 is the BHF.

Similarly for CRES, the significant terms that could be included in the regression model are those with p-value <0.05, hence the following equation was developed:

$$\text{Burr height} = 0.0477 + 0.002095X_1 - 3 \times 10^{-6}X_3 + 0.000001X_1X_3 \quad \text{(Eq 4)}$$

where X_1 is the clearance (mm); X_2 is the thickness (mm); and X_3 is the BHF.

The signs of the parameters in these models can be examined for the type of relation with response. Positive signs mean the response output value that will go in the same direction as the parameter, and negative signs imply the opposite. To test the prediction performance of the regression models the absolute relative error (ARE) was computed based on experimental and predicted values. The ARE is computed based on the following equation:

$$\text{ARE}(\%) = \frac{|\text{Predicted value} - \text{Experimental value}|}{\text{Experimental value}} \quad \text{(Eq 5)}$$

For the second order model, the maximum ARE in the case of carbon steel was about 33.96% while average ARE was about 15.18% for CRES, maximum ARE was 33.25% while the average ARE was 14.22%. It will be an advantage if we can get these errors reduced. This leads us to use ANN for prediction purposes instead of MRA because it has the tendency to account for hidden trends and relations between inputs and outputs.

5.2 Response Surface Methodology

Response surface method was used as a graphical representation of the second order regression model. See Fig. 5(a) for 3-D representation. Figure 5(b) shows the contour plot of the variation of response (burrs height) with changing of both

Table 4 Second order regression model for CRES

Term	Coefficient	SE coef.	*T*	*p*
Constant	0.047653	0.006974	6.833	0
Clearance	0.002095	0.000176	11.894	0
Thickness	0.019713	0.020956	0.941	0.354
BHF	−3E−06	0.000001	−4.016	0
Clearance*clearance	0.000001	0.000004	0.375	0.71
Thickness*thickness	−0.01558	0.015878	−0.981	0.334
Clearance*thickness	−0.0002	0.000201	−0.972	0.338
Clearance*BHF	0.000001	0	60.21	0
Thickness*BHF	0	0.000001	0.108	0.915

$S = 0.00100419$; PRESS = 0.0000551503; $R^2 = 99.92\%$; R^2(pred) = 99.85%; R^2(adj.) = 99.89%

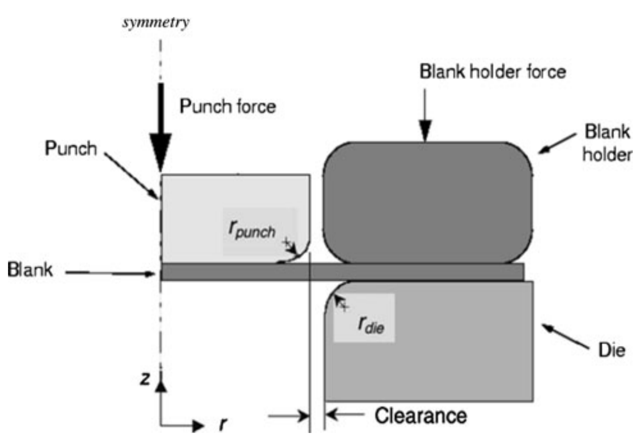

Fig. 4 Schematic representation of the blanking process (Ref 6)

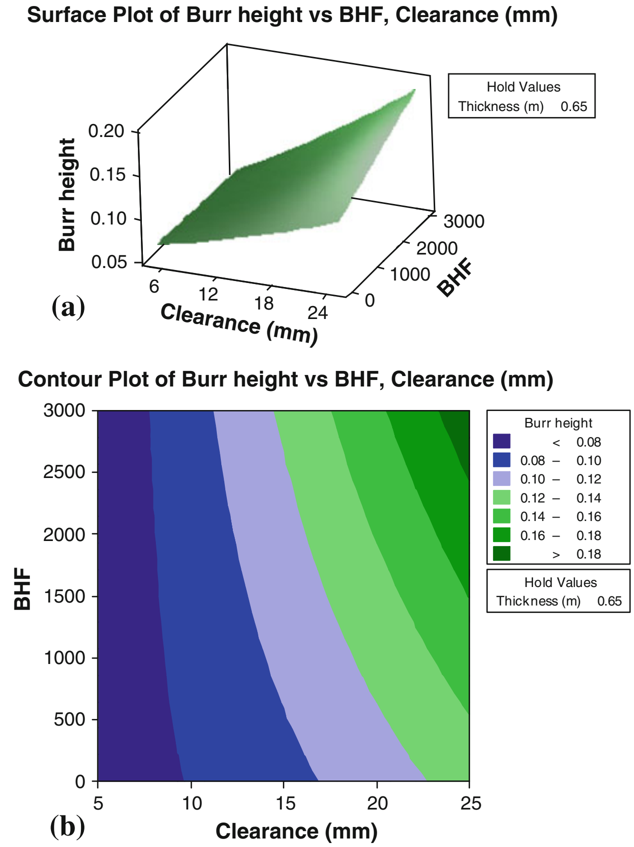

Fig. 5 (a) 3-D response surface for carbon steel using second order regression models; (b) contour plot of the burrs height as a function of clearance and BHF (Thickness was hold at a nominal value of 0.65 mm)

clearance and BHF for carbon steel. It can be concluded that burrs height is strongly influenced by clearance (Thickness was fixed at nominal value of 0.65 mm).

In the modeling of blanking process, interaction between the parameters also plays a leading role. An interaction occurs when the response changes from a given level of factor combination to another. That is, the effect of one factor is dependent upon a second factor. In the present study, among the factors interactions considered for burrs height, the clearance-BHF interaction seems significant at 95% confidence level. This means that the clearance depends on blank-holder force. On the other hand, clearance-thickness and thickness-BHF are insignificant at this confidence level. Estimated response surface for burrs height with relation to the design parameters of clearance and BHF is shown in Fig. 5(a). It can be seen from this figure, the burrs height tends to increase considerably with increase in clearance. However, increasing BHF values do not greatly affect burrs height. Hence, lowest possible burrs height is obtained at low clearance values (below 13%) and a low combination values between clearance and BHF. Similar trend as that of carbon steel was noticed in case of CRES where a lower burrs height can be obtained by using low values of clearance and BHF. This can be seen in Fig. 6(a) and (b).

5.3 Artificial Neural Networks Results

As mentioned before, the ANNs were constructed with three inputs: clearance (mm), sheet metal thickness (mm), and BHF (N). Two hidden layers were used in each ANN, and one output node; burrs height (mm). The number of neurons in the hidden layer is determined experimentally by selecting some hidden neuron numbers where the goal is to optimize the learning curve with lowest possible error and lowest training cycles. In this study, a trial and error method is performed to optimize the number of neurons in the hidden layers. It was found that the best ANN structure is that with two hidden layers (seven neurons in the first hidden layer and four neurons in the second hidden layer) in the case of carbon steel. This gives ANN architecture of (3-7-4-1) (Fig. 7). Similarly in the case of CRES, the following architecture (3-7-7-1) fitted well (Fig. 8).

A data set consists of 40 experimental data points for each material (40 experimental points for carbon steel and 40 experimental examples for CRES) were used to construct fully developed feed forward back propagation networks. Among these 40 data point, 30 examples were used as training examples and the remaining were used in testing process. For the training problem at hand the following parameters were found to give good performance and rapid convergence of the NN: sigmoid logistic was chosen as activation function between all layers, learning rate and momentum were selected experimentally to be 0.45 and 0.15, respectively, in the case of carbon steel and 0.6 and 0.07, respectively, in the case of CRES. The training process was terminated after 401 and 601 cycles for carbon steel and CRES, respectively. Testing of the trained network was set to one testing cycle per 100 training

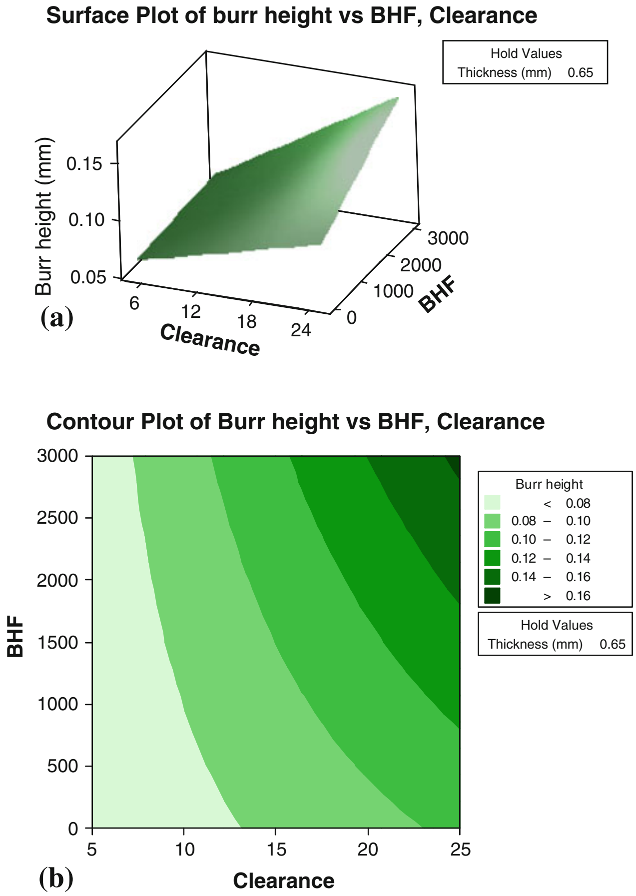

Fig. 6 (a) 3-D response surface for CRES using the second order regression model; (b) contour plot of the burrs height as a function of clearance and BHF (Thickness was hold at a nominal value of 0.65 mm)

cycles. Testing datasets are used to examine how the networks are efficient in predicting the new unseen points. If the network predictability is good enough then the training and testing processes will be terminated, if not then the ANN will run the training and testing processes to reach threshold error. When the training and testing process were finished, the averaged errors were 0.004691 and 0.002361 for carbon steel and CRES, respectively.

To test the generalization performance of the trained network in training and testing processes, the experimental values were compared to the predicted values resulted from ANN as shown in Fig. 9 and 10. These two figures show a good match between experimental and predicted values. Once the training and testing processes are finished, the ANN can be recalled to do prediction effectively. To do so, it was found that the average ARE was 2.20% and the highest relative absolute error was 10.38% for carbon steel. Similarly, the average ARE was 4.85% and the highest relative absolute error was 10.24% for CRES. Table 5 summarizes the different parameters of the ANNs.

5.4 Comparison Between MRA and ANN Prediction Models

Now, which prediction method is better and when each one should be used to predict and optimize the blanking process? In the case of developing empirical relations, MRA model is preferred over ANN model because it is an explicit model while the ANN model is a black box. In the other direction, when data are sparse or not generated from designed experiments, MRA may not be able to produce a better model than ANN, then the ANN modeling method and its associated model may be preferred to the MRA method and its model if such a model is available.

Figures 11 and 12 show a comparison between experimental values versus predicted values with ±10% error interval resulted from MRA and ANN (testing dataset) for carbon steel

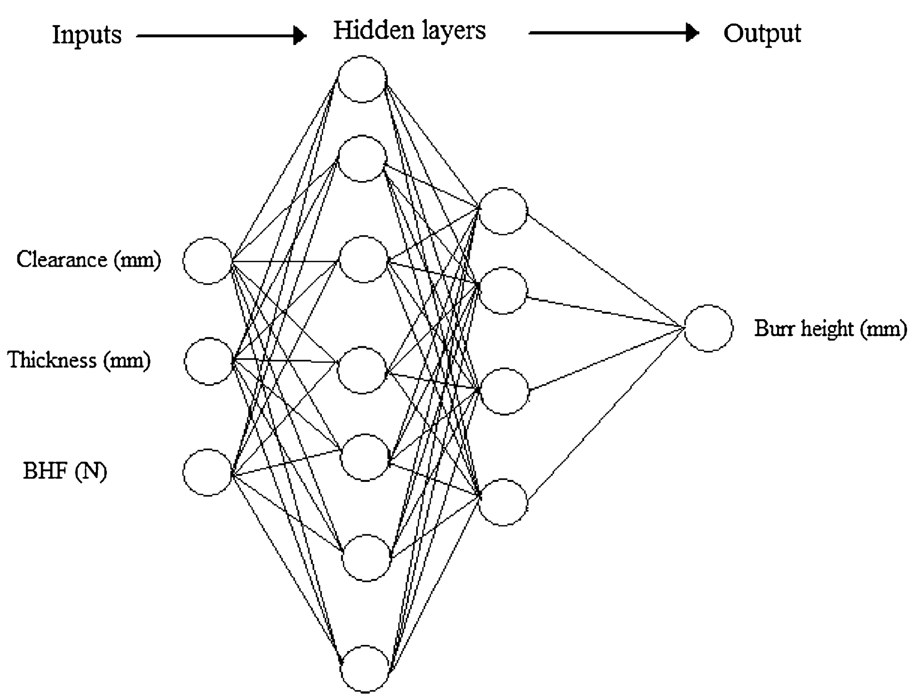

Fig. 7 Artificial neural network structure for carbon steel (3-7-4-1)

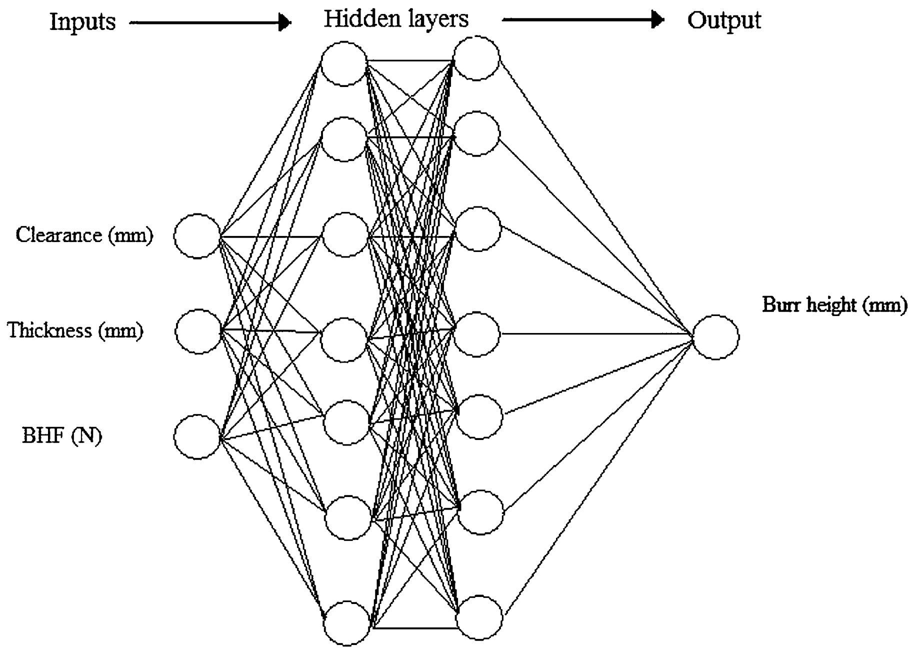

Fig. 8 Artificial neural network structure for CRES (3-7-7-1)

Table 5 Summary of the ANNs parameters

Neural network parameters	First ANN (carbon steel)	Second ANN (CRES)
Network architecture	3-7-4-1	3-7-7-1
Number of hidden layer	2	2
Transfer function	Sigmoid: input-1st hidden layer-2nd hidden layer-output layer	Sigmoid: input-1st hidden layer-2nd hidden layer-output layer
Number of training examples	30	30
Number of testing examples	10	10
Learning rate	0.45	0.15
Momentum factor	0.6	0.07
Number of epochs	401	601
Mean squared error (MSE)	0.004691	0.002361

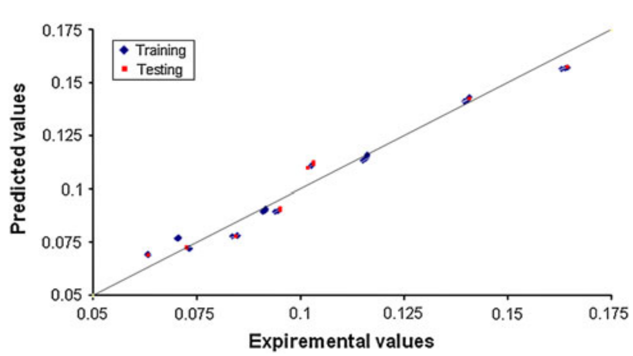

Fig. 9 Experimental versus predicted values of burrs height for CRES

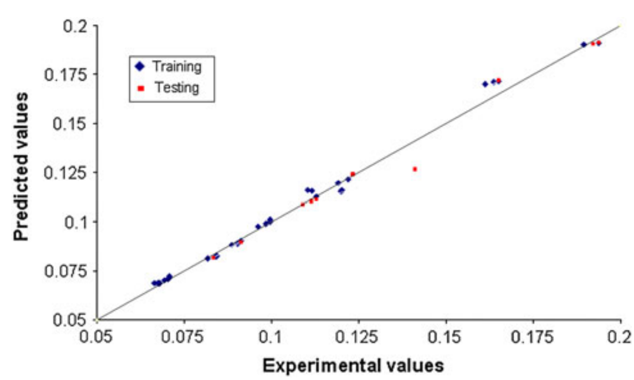

Fig. 10 Experimental versus predicted values of burrs height for carbon steel

and CRES, respectively. This selection is based on the complete randomness during training of ANNs and testing dataset usually has the higher error levels. Again, ANN seems more efficient in prediction when compared to MRA because it efficiently handles nonlinear relations between different inputs and outputs even if this nonlinearity does not follow any known curve.

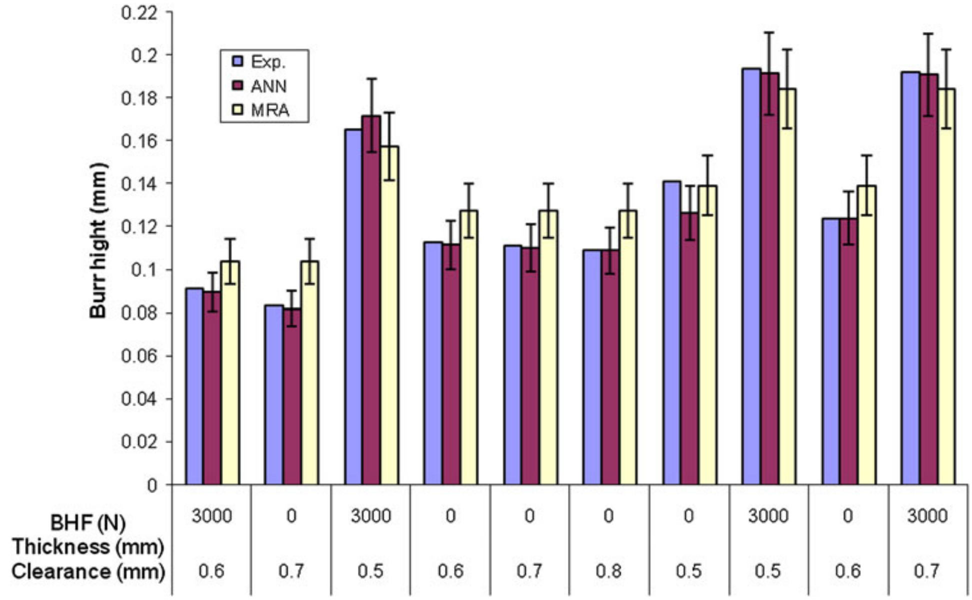

Fig. 11 Burrs height experimental versus predicted values from MRA and ANN for carbon steel

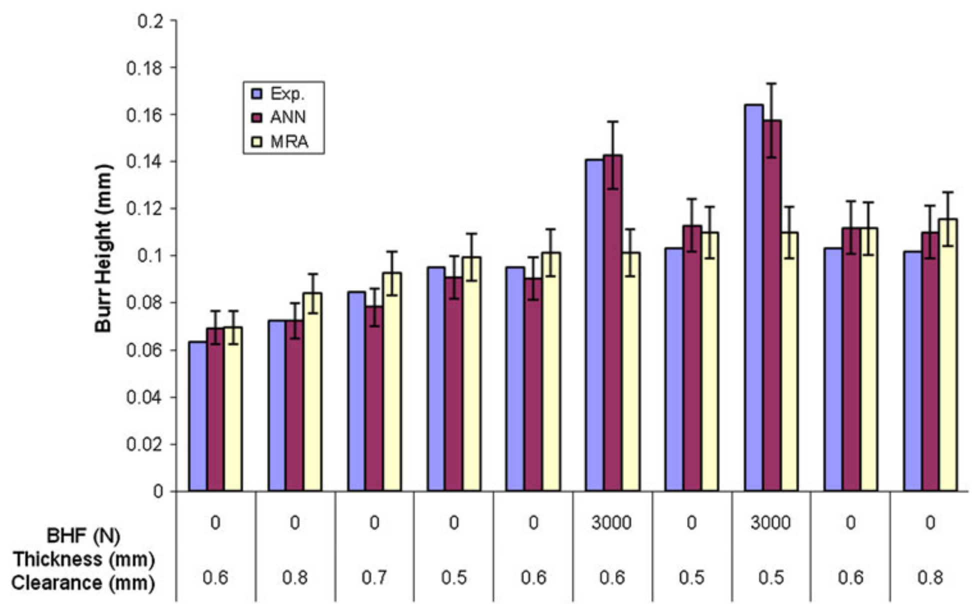

Fig. 12 Burrs height experimental versus predicted values from MRA and ANN for CRES

6. Conclusions

In this study, MRA and feed forward backpropagation ANN have been used for prediction of the burrs height in blanking process under different process parameters. Modeling the blanking process using MRA and ANN approaches provides a systematic and effective methodology for the prediction. Both MRA and ANN revealed that clearance and BHF were the important factors that influence the response.

The results of ANN models show close matching between the model outputs and the experimental outputs. Hence, this model can be used efficiently for prediction potentials for non-experimental pattern which in turn save experimental time and cost. It was shown that ANN performs well in mapping nonlinear relationship between inputs and outputs. If both MRA and ANN models considered they will provide statistically satisfactory prediction results. ANN methodology consumes lesser time and gives higher accuracy. Hence, modeling the blanking process using ANN is more effective compared with MRA. The developed modeling methods in this article can aid the prediction, optimization, and improvement of blanking process and the selection of proper parameters for each engineering material.

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