International Journal of Mechanics and Energy (IJME)
Vol. 2, Issue 4, 2014, ISSN: 2286-5845

Cutting Forces Prediction in Turning by Technique of ANNs

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Abstract: In this study, we develop a robust ANN technique to predict cutting force components during hard turning of an AISI 52100 steel using CBN cutting tool. The training network is performed on 20 pairs of input-output experimental dataset where cutting parameters and workpiece hardness are taken as the input dataset. Back-propagation training is performed by using Bayesian Regularization in combination with Levenberg-Marquardt algorithm. The optimal network architecture is determined after several simulations by MATLAB Neural Networks Toolbox and it is consisting of 8 neurons in hidden layer. The developed model was verified with other experimental test data not used in training; for this purpose, the maximum average MAPE value of 11.79 % was obtained for the cutting forces prediction.

Key words: Artificial neural network, cutting force components, hard turning, machining process.

1. Introduction

Hard machining processes produces high cutting forces and temperatures that affect cutting process, such as dynamic stability, tool wear, workpiece surface integrity, geometrical tolerances and machining times. Cutting forces are factors that manufacturers must be able to control to ensure better performances. Modeling of cutting forces is one of the major problems in metal cutting theory. Many machining parameters influence greatly on cutting forces so it is quite difficult to develop a proper theoretical model to describe efficiently the machining process.

The Artificial Neural Network (ANN) approach is routinely considered as an accurate and powerful tool for modeling of machining processes.

The capacity of ANNs to make nonlinear relationships in a relatively efficient manner has motivated some researchers for modeling much process such as turning, milling and drilling. A large number of applications of ANN models to predict cutting forces are also reported in literature [1-5].

Szecsi [6] developed an approach for modeling cutting forces, feed-forward multilayer neural network trained by Back Propagation (BP) error algorithm. The training network is performed by experimental machining data.

Zuperl and Cus [7, 8] developed supervised ANN approach to estimate forces generated during end milling process. They have found that radial basis network require more neurons than standard feed-forward neural network with BP learning rule, but conceiving of radial basis neural network lasts only a part of time necessary for training of feed-forward network.

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Hao et al. [9] introduced a model for Self-Propelled Rotary Tool (SPRT) cutting forces prediction using ANN. Two models are presented of determining the connection weights by BP algorithm and hybrid of Genetic Algorithm (GA) with BP.

Another approach is used by Aykut et al. [10] to predicted cutting forces as function of cutting parameters for face milling of satellite 6 using an ANN. The training of the network is performed using Scaled Conjugate Gradient (SCG) feed-forward BP algorithm.

In recent studies, Makhfi et al. [11] proposed multilayer feed-forward ANN with BP training by Levenberg–Marquardt algorithm to predict cutting force components in hard turning. The best network architecture is extracted by calculating a mean square error and regression coefficient. The developed model network was verified with other experimental test data not used in training. The percentage test error is less than 15 %.

In this work, an ANN technique is proposed to predict cutting force components in hard turning of an AISI 52100 bearing steel using CBN cutting tool. Workpiece hardness HRc (MPa) and cutting parameters such as speed V_c (m/min), feed-rate f (mm/rev) and dept-of-cut a_p (mm) are taken as input dataset of the ANN model while cutting force components such as cutting-force F_t (N), feed-force F_a (N) and radial-force F_r (N) are the output dataset.

Figure 1 shows the cutting parameters and the cutting force components in turning process.

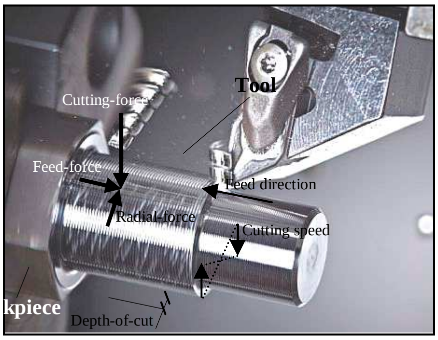

Fig. 1 Cutting force components in turning process

The architecture of the neural network model is described as follows.

2. Neural network model

The neural network approach is an effective technique based on the statistical regression. It can be used in various fields of engineering for modeling complex relationships which are difficult to describe by utilizing physical models.

An artificial neural network consists of simple processors called neurons interconnected. This hierarchical network structure has an input vector receiving input data and an output layer which sends final information to users. In middle stand hidden layers which have no direct contact with the environment. The input-output dataset for our ANN model are illustrated in Figure 2.

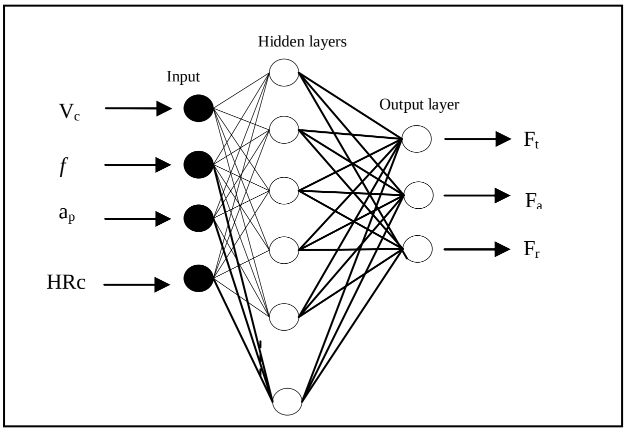

Fig. 2 Multilayer feed-forward ANN architecture

The mathematical principle of the neuron is shown in Figure 3.

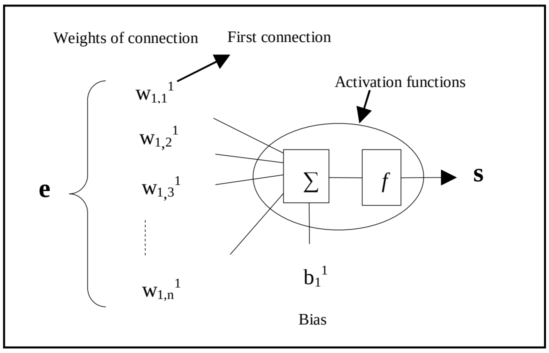

Fig. 3 Mathematical model of neuron

The training of the ANN is performed on 20 pairs of input-output experimental dataset as shown on Table 1.

Table 1 Training dataset [12]

Test no.	Cutting parameters				Experimental forces		
	HRc (MPa)	V_c (m/min)	f (mm/rev)	a_p (mm)	F_a (N)	F_r (N)	F_t (N)
1	45	100	0.1	0.2	56	104	128
2	45	150	0.08	0.2	28	69	75
3	45	150	0.1	0.4	82	129	174
4	45	150	0.2	0.38	40	120	151
5	50	100	0.1	0.2	41	111	106
6	50	150	0.2	0.2	58	193	168
7	50	200	0.1	0.2	36	97	94
8	52	50	0.1	0.2	44	103	117
9	52	100	0.1	0.2	40	97	91
10	52	150	0.1	0.2	38	102	98
11	52	250	0.1	0.2	37	97	95
12	52	300	0.1	0.3	59	112	135
13	54	100	0.1	0.2	34	85	96
14	54	150	0.1	0.3	57	115	131
15	54	150	0.1	0.4	83	142	172
16	54	150	0.15	0.2	40	110	128
17	54	200	0.1	0.2	35	91	92
18	56	50	0.1	0.2	51	141	121
19	56	150	0.1	0.2	30	75	86
20	56	250	0.1	0.2	33	78	93

Their generalization capacity are evaluated on 5 further pairs of input-output test dataset (see Table 2) that were not been used in training dataset.

Table 2 Testing dataset [12]

Test no.	Cutting parameters				Experimental forces		
	HRc (MPA)	V_c (m/min)	f (mm/rev)	a_p (mm)	F_a (N)	F_r (N)	F_t (N)
1	45	150	0.15	0.2	42	115	136
2	50	150	0.15	0.2	46	139	137
3	52	200	0.10	0.2	36	95	96
4	54	150	0.10	0.2	32	91	94
5	56	100	0.10	0.2	33	81	96

Notice that the utilized ANN model consists of multilayer feed-forward: input, hidden and output layers. The selection of the training algorithm, activation functions in the hidden layer and output layer, number of hidden layers and neurons in hidden layer are very important to obtain the best prediction results. Detailed information concerning ANNs can be found in [13]. Using double hidden layer has shown neither advantage over single hidden layer [14]. Before training the network, the original values which are the set of input-target vectors are normalized in the range of -1 to 1 for efficient processing by the networks.

Back-propagation by Bayesian Regularization in combination with Levenberg–Marquardt algorithm is employed for training neural networks. Since, it has proved to be an excellent universal approximator of non-linear functions [15, 16].

The basic goal in training is to minimize the overall error of the network between target data and network output data during training, and then the best network structure was determined [14-17]. The training is stopped when the validation error reaches a minimum value, once the network training is successfully finished.

The optimal network architecture is obtained from a sigmoid activation function in the hidden layer and a linear activation function in output layer. These activation functions give the outputs of the neuron. In the training process, weights and biases of the network are initialized to small random values to avoid sharp saturation in the activation functions. The BP training methodology used for training neural networks is summarized below.

Refer to the architecture of ANN given by Figure 2, the output response is calculated as follows:

$$s = f(We + b) \tag{1}$$

The performance evaluation of the optimum network architecture is determined by overall calculated statistical error values as SSE (Sum Squared Error) and SSW (Sum Squared Weights) under MATLAB Neural Networks Toolbox for the ANNs approaches between target data and network output data during training and testing. Additionally, to find out the optimal network architecture, linear regression coefficient R (equation 2) and Mean Absolute Percentage Error

MAPE (3) between ANN prediction and experimental values are used to evaluate the statistical performance of the networks for training and testing phases.

$$R=\frac{\sum_{k=1}^{Q}(c(k)-\bar{c})(s(k)-\bar{s})}{\sqrt{\sum_{k=1}^{Q}(c(k)-\bar{c})^2}\sqrt{\sum_{k=1}^{Q}(s(k)-\bar{s})^2}} \tag{2}$$

Were Q is the number of cutting conditions. $\bar{c}$ and $\bar{s}$ are mean target and output values.

$$MAPE=\frac{c-s}{s}.100\% \tag{3}$$

The number of neurons in the hidden layers is varied in different experiments in training and is found with statistical error values. The optimal network architecture is determined after several simulations by MATLAB Neural Networks Toolbox.

3. Results and Discussions

In order to define the best architecture, a various number of neurons in hidden layer have been tested, from 2 to 20 with step of 2.

To evaluate the accuracy of the selected structure, cutting force components are finally evaluated for 5 additional cutting conditions that are not used for training the network but that are in the same range as those used for training. To find the optimal ANN four representative criteria are adopted for each structure and collected in Table 3.

Table 3 Statistical error values

ANN architectures	SSE	SSW	R Training	R Testing
4-2-3	3.55	30.8	0.895	0.982
4-4-3	0.89	81.7	0.975	0.988
4-6-3	0.11	135	0.997	0.978
4-8-3	0.05	141	0.999	0.978
4-10-3	0.06	134	0.998	0.983
4-12-3	0.06	132	0.998	0.981
4-14-3	0.05	137	0.999	0.984
4-16-3	0.05	136	0.999	0.983
4-18-3	0.05	137	0.999	0.984
4-20-3	0.06	132	0.998	0.981

The evolution of SSE value as a function of SSW value is plotted on Figure 4. The BR/LM algorithm during training converges if the SSE and the SSW are relatively constant over several iterations; the error of the network is minimized and then the best network architectures are selected.

A convergence area can be noticed as the number of neurons in hidden layer reaches 8. From this result, the best structure is chosen in this area where SSE is slightly close to 0 and SSW is between 132 and 141.

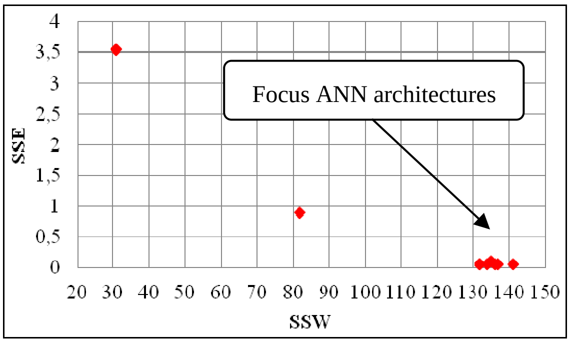

Fig. 4 Decrease of SSE during training of different neural networks

The index R of the training and testing are used in this analysis to judge the training and testing performances. It can also be seen from Table 3 that increasing the number of neurons from 10 to 20 has no significant improvement on the performances of the network. The network architecture consisting of 8 neurons in hidden layer is chosen as the optimum ANN model.

Figure 5 illustrates a graphical comparison between experimental and predicted cutting forces.

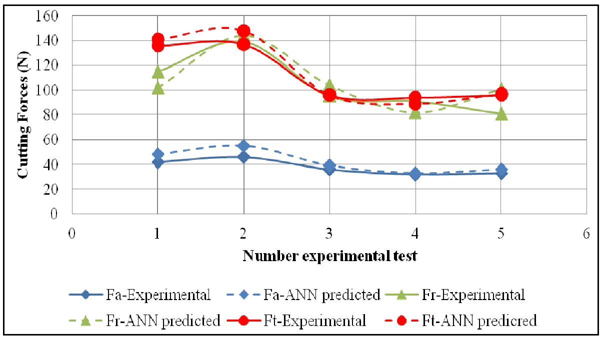

Fig. 5 Correlation between experimental and predicted cutting forces

Table 4 gives a numerical comparison between experimental and predicted cutting force components.

Table 4 Comparison between experimental and predicted values of cutting forces

Test no.	Experimental cutting forces			Predicted cutting forces			MAPE (%)		
	F_a (N)	F_r (N)	F_t (N)	F_a (N)	F_r (N)	F_t (N)	F_a	F_r	F_t
1	56	104	128	55	105	128	1.79	0.96	0.00
2	28	69	75	28	69	76	0.00	0.00	1.33
3	82	129	174	82	129	174	0.00	0.00	0.00
4	40	120	151	40	120	151	0.00	0.00	0.00
5	41	111	106	42	112	105	2.44	0.90	0.94
6	58	193	168	58	192	168	0.00	0.52	0.00
7	36	97	94	36	96	93	0.00	1.03	1.06
8	44	103	117	45	102	115	2.27	0.97	1.71
9	40	97	91	38	96	98	5.00	1.03	7.69
10	38	102	98	37	102	94	2.63	0.00	4.08
11	37	97	95	37	97	96	0.00	0.00	1.05
12	59	112	135	59	113	135	0.00	0.89	0.00
13	34	85	96	35	88	95	2.94	3.53	1.04
14	57	115	131	58	114	131	1.75	0.87	0.00
15	83	142	172	83	142	172	0.00	0.00	0.00
16	40	110	128	40	111	127	0.00	0.91	0.78
17	35	91	92	35	91	92	0.00	0.00	0.00
18	51	141	121	50	140	121	1.96	0.71	0.00
19	30	75	86	30	75	87	0.00	0.00	1.16
20	33	78	93	33	78	93	0.00	0.00	0.00
Average MAPEs							**1.039**	**0.616**	**1.042**

As expected, the developed ANN model gives precise results for the prediction of cutting force components used in training; average MAPEs of 1.039 %, 0.616 % and 1.042 % are respectively noted on F_a, F_r and F_t.

Table 5 illustrates cutting conditions used to test the developed model as well as the corresponding experimental and predicted cutting force components.

Table 5 Comparison between experimental and predicted values in testing

Test no.	Experimental forces			Predicted forces		
	F_a (N)	F_r (N)	F_t (N)	F_a (N)	F_r (N)	F_t (N)
1	42	115	136	48	102	141
2	46	139	137	55	144	148
3	36	95	96	39	104	96
4	32	91	94	33	82	89
5	33	81	96	36	101	97

Average MAPEs values of F_a, F_r and F_t are given in Table 6.

Table 6 MAPE values between network predictions and experimental values in testing

MAPE (%)		
F_a	F_r	F_t
14.29	11.30	3.68
19.57	3.60	8.03
8.33	9.47	0.00
3.13	9.89	5.32
9.09	24.69	1.04
10.88	**11.79**	**3.61**

The average MAPEs of 10.88 %, 11.79 % and 3.61 % are respectively noted on F_a, F_r and F_t.

4. Conclusions

The objective of this study is to develop a robust approach for prediction of cutting force components in hard turning of AISI 52100 bearing steel using CBN cutting tool as functions of cutting conditions.

ANN training is performed on an experimental machining dataset of 20 cutting conditions and then the numerical model accuracy is evaluated on a test dataset of 5 values not used in training. Back-propagation training is performed by using Bayesian Regularization in combination with Levenberg- Marquardt algorithm. A sigmoid activation function is chosen in hidden layer and a linear one in output layer. Five criteria are used to evaluate the efficiency of each result: SSE, SSW, linear regression coefficient R at the training and testing, and MAPE between ANN predictions and experimental values. A various number of neurons in hidden layer are tested from 2 to 20 with step of 2. It is noticed that the algorithm converges when this number reaches 8.

An excellent agreement is found between experimental and numerical predictions dataset for the 20 cutting conditions used in training and the 5 cutting conditions used in testing data. Finally, the accuracy of the developed ANN model is in good agreement with that obtained in literature [7, 8, 10 and 11].

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