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A CASCADE CORRELATION NEURAL NETWORKS FOR THE PREDICTION OF SURFACE FINISH IN DRY TURNING OF SS 420 MATERIALS

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ABSTRACT

In the contribution, a cascaded correlation neural network optimization technique for optimization of cutting parameters for predicting the surface roughness is proposed. The cascaded correlation neural network algorithm has the powerful capabilities of learning and adaptation. Cascade-Correlation is a new architecture and supervised learning algorithm for artificial neural networks. Instead of just adjusting the weights in a network of fixed topology, Cascade-Correlation begins with a minimal network, then automatically trains and adds new hidden units one by one and creating a multi-layer structure. The Cascade-Correlation architecture has several advantages over existing algorithms: it learns very quickly, the network determines its own size and topology and it retains the structures it has built even if the training set changes. The validation of the methodology is carried out for dry turning of SS420 steel using uncoated tungsten carbide tools. It is observed that the present methodology is able to make accurate prediction of surface roughness by utilizing small sized training and testing datasets.

Key words: *Cascaded Correlation Neural Network. Taguchi Methods and Surface Roughness*

1. Introduction

The significance of machining process has been increased through rapid development of manufacturing industry. In machining, cutting fluid may be considered as the prime factor. However the use of such cutting fluid may seriously degrade the environment. This gives rise to the serious problems of procurement, storage, disposal and maintenance and cost of the cutting process [1]. So getting the possible surface finish through dry machining while considering the various tool positions has been one of the challenging works.

Turning is one of the most widely used metal removal operations in industry in view of its capability to yield a high metal removal rate and achieve a reasonably good surface quality. It has a large number of applications in industries such as the aerospace and automotive sectors, where quality is an important factor in the production of slots, pockets, precision moulds and dies.

Two main attributes of job quality are surface roughness and dimensional deviation. Surface finish has a great influence on the reliable functioning of two mating parts. Surface roughness is defined as the irregularities of any material resulting from machining operations. Average roughness Ra is theoretically derived as the arithmetic average value of departure of the profile from the mean line along a sampling length [2]. Surface roughness depends on process parameters (like cutting velocity, feed rate, depth of cut etc) tool geometry (like rake angle, nose radius etc) and machining irregularities such as chatter, wear, material properties and cutting fluid. In case of dry machining greater amount of thermal stress is developed on tool and work piece material as they rub against each other. Thus to pursue dry machining such disadvantages should be compensated. The possible approach is to adjust the process parameters and tool geometry in order to get the optimum surface finish.

In turning, the quality of the generated surfaces is mainly evaluated by its roughness. In fact, previous investigations have shown wide correlations between this characteristic and the other parameters characterizing the surface integrity including fatigue life and corrosion resistance [3, 4].

Surface finish in turning is found to be influenced in varying amounts by a number of factors, such as feed rate, work material characteristics, work hardness, unstable built up edge, cutting speed, depth of cut, time of cut, tool nose radius, tool angles, stability of the machine tool and work piece set-up, use of cutting

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fluids etc. Various researchers studied the influence of few out of the above mentioned several factors on the surface finish. Albrecht [5] investigated the effect of speed, feed, depth of cut and nose radius on the surface finish of a steel work-piece. Ansell and Taylor [6] have studied the effect of tool material on the surface finish of a cast-iron work-piece. Chandiramani and Cook [7], in their investigation on the effect of varying cutting speeds on the surface finish, found an intermediate region of deterioration on surface finish due to the formation of built up edge. Karmakar [8], however, did not observe this in a study with ceramic tools. Dixit and Chandra [9] developed a strategy for choosing the network parameters as well as training and testing data for predicting upper, lower and most likely estimates of roll force and roll torque in a cold flat rolling process. The present work employs a similar methodology for predicting the surface roughness in a turning process. Chryssolouris and Guillot [10] compared the neural network model with the regression model and observed the superiority of former. On the other hand, Feng and Wang [11] found multiple regression models and neural network models to be equally effective. The Artificial Neural Networks (ANN) has been a predominant technology for intelligent control for many years [12, 13, 14]. By virtue of the learning ability, neural networks can be adapted to constantly changing environments. The cascaded correlation neural networks prove to be a powerful technique for various applications [15, 16].

In this paper an adaptive Cascaded Correlation Artificial Neural Network (CCANN) algorithm is developed [17] for predicting the surface roughness in turning of SS420 material. Since the training and testing data are collected from experiments, there may be some noisy data due to randomness of the process and measurement errors. A data filtration scheme is employed to eliminate spurious data. The proposed methodology has been validated using experimental data on dry turning of steel using uncoated tungsten carbide tools.

2. Prediction of Surface Roughness

Present section reports the study of surface finish of turned SS420 material. A cascaded correlation neural network trained using the back propagation algorithm has been employed. The process parameters considered are cutting speed (*V*), feed (F) and depth of cut (D) and nose radius (R). Thus, the input layer of the neural network contains four neurons while the output layer has a single neuron corresponding to the predicted value of surface roughness (Ra). The accuracy, reliability and effectiveness of the neural network depends on a number of factors like number of training and testing data, learning rate, number of hidden layers, number of neurons in the hidden layers and processing function used.

2.1 Experimental procedure

The experiment is performed in SS 420 of size 25 mm diameters which contains 12% of chromium sufficient enough to give corrosion resistance property and good ductility. Its chemical composition is given as minimum of 0.15% C, 12.0-14.0% Cr, < 1.0% Si , <0.04% P ,<1.0% Mn, <0.03% S remaining as Fe . In this process four factors at three levels are chosen for feed, speed, depth of cut and tool nose radius ranges from 0.059-0.26 mm/rev, 39-94 m/min, 0.4- 1.2 mm and 0.4-1.2 mm respectively. The different sets of experiments are performed using a Kirloskor centre lathe. The machined surface is measured at three different positions and the average values are taken using a RUGOSURF 10G surface texture measuring instrument.

3. Methodology

3.1 ANN implementation

Artificial Neural Network is a high speed online computational technique, which are trained through an offline algorithm using example pattern which can provide an output corresponding to a new pattern without any iteration in real time. The cascade correlation network is a constituent algorithm, proved better than conventional algorithm [18].

3.2 The cascade correlation algorithm

3.2.1 Initial configuration

The algorithm begins with a simple perceptron with N input units and M output units. N and M are chosen on the basis of the problem that the network is to learn.

3.2.2 Initial training

The perceptron is trained on the entire training set {(Vp, Tp) | p = 1, . . P}, until the performance of the network is as good as possible. If the desired performance is obtained, the algorithm stops. Otherwise: Start adding hidden units to the network, one by one.

3.2.3 Training of candidates

A pool of candidates for a new hidden unit is generated. This pool emulates a stochastic search in the weight space, which will decrease the risk of inserting a candidate stranded in a local minimum with high error.

Each node in the pool of candidates is connected to all input nodes and all previously inserted hidden units. Each of the candidates is trained with the purpose of maximizing some measure of "goodness" of the candidate.

3.2.4 Inserting a new hidden unit

The candidate with the highest score is inserted "for real" in the network as a new hidden unit. The incoming weights to the new hidden unit are then frozen, i.e. they are not to be changed anymore. The new hidden unit is connected to all output nodes with random weights.

3.2.5 Retraining the network

All the incoming weights to the output units are retrained in order to adjust the weights from the newly inserted hidden unit. If the performance of the network is satisfying after retraining, the algorithm stops. Otherwise: Go to 3.2.3.

3.3 Cascade correlation neural network architecture

A cascade correlation network consists of input units, hidden units, and output units. Input units are connected directly to output units with adjustable weighted connections. Connections from inputs to a hidden unit are trained when the hidden unit is added to the net and are then frozen. Connections from the hidden units to the output units are adjustable consequently. Cascade correlation network starts with a minimal topology, consisting only of the required input and output units (and a bias input that is always equals to 1). This net is trained until no further improvement is obtained. The error for each output is then computed (summed over all training patterns). Next, one hidden unit is added to the net in a two step process. During the first step, a candidate unit is connected to each of the input units, but is not connected to the output units. The weights on the connections from the input units to the candidate unit are adjusted to maximize the correlation between the candidate's output and the residual error at the output units. The residual error is the difference between the target and the computed output, multiplied by the derivative of the output unit's activation function, i.e., the quantity that would be propagated back from the output units in the back propagation algorithm. When this training is completed, the weights are frozen and the candidate unit becomes a hidden unit in the net. The second step in which the new unit is added to the net now begins. The new hidden unit is then connected to the output units, and the weights on the connections being adjustable. Now all connections to the output units are trained. (Here the connections from the input units are trained again, and the new connections from the hidden unit are trained for the first time.) A second hidden unit is then added using the same process. However, this unit receives an input signal from the both input units and the previous hidden unit. All weights on these connections are adjusted and then frozen. The connections to the output units are then established and trained. The process of adding a new unit, training its weights from the input units and the previously added hidden units, and then freezing the weights, followed by training all connections to the output units, is continued until the error reaches an acceptable level or the maximum number of epochs (or hidden units) is reached.

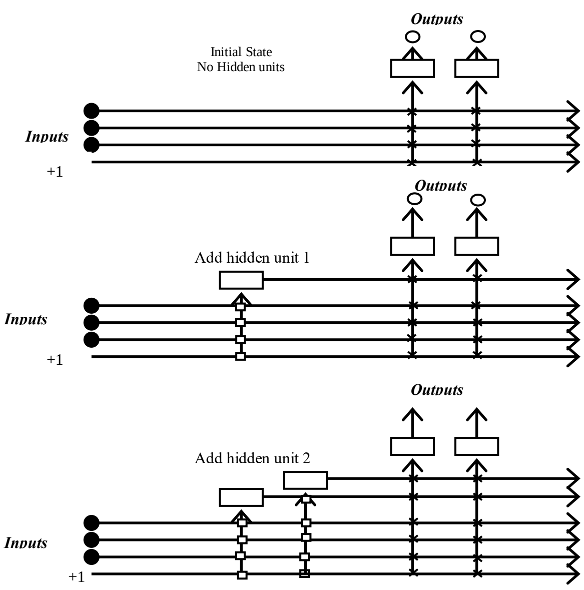

Fig. 1 Cascade Architecture for Initial State and after Adding Two Hidden Units

The purpose of inserting a new unit is to reduce the total error of the network. The way the Cascade-Correlation architecture does this is to train the candidate unit so the correlation between the residual error and the output from the candidate is maximized. Let X and Y be two stochastic variables.

Then the correlation between X and Y is defined as:

$$Corr[X,Y] = \frac{Cov[X,Y]}{\sqrt{Var[X]Var[Y]}}$$

3.4. Proposed cascaded correlation neural networks based optimization

In this implementation, a novel-learning algorithm, termed cascaded correlation neural network learning algorithm is proposed. The proposed learning

Table 1: Training and Testing Data of Experiments by CCANN

Experiment	Feed	Depth of cut	Cutting velocity	Nose radius	Actual Surface roughness	Predicted Surface Roughness	Error	Error Percentage (%)
pruns	F	DOC	V	R	Ra	Ra		
	mm/rev	mm	m/min	mm	microns	microns		
1	1	1	1	1	1.46	1.459	-0.0002195	-0.015039907
2	1	2	2	2	0.972	0.971	-0.0015829	-0.162745815
3	1	3	3	3	1.619	1.619	0.0006616	0.040859512
4	1	1	2	3	0.891	0.891	0.0000349	0.006443714
5	1	2	3	1	1.872	1.871	-0.0007161	-0.038256409
6	1	3	1	2	2.676	2.676	-0.0000749	-0.002593464
7	1	1	3	2	1.308	1.309	0.0013658	0.104420774
8	1	2	1	3	0.872	0.872	-0.0000516	-0.000837301
9	1	3	2	1	1.347	1.347	0.0003021	0.022422922
10	2	1	2	3	1.331	1.33	-0.0012833	-0.096394892
11	2	2	3	1	2.224	2.229	0.0049248	0.221374917
12	2	3	1	2	1.915	1.915	0.0003537	0.018468845
13	2	1	3	2	1.133	1.135	0.0014952	0.131893438
14	2	2	1	3	1.233	1.233	-0.0001112	-0.00901
15	2	3	2	1	1.966	1.966	0.0005825	0.029628217
16	2	1	1	1	2.05	2.05	0.000007	0.000318653
17	2	2	2	2	1.77	1.768	-0.0002035	-0.109586264
18	2	3	3	3	1.3	1.299	0.0012991	-0.015656251
1[a]	3	1	3	2	3.201	3.202	-0.0019396	0.040585637
2[a]	3	2	1	3	1.754	1.754	0.0003817	0.021764182
3[a]	3	3	2	1	4.912	4.912	-0.000868	-0.017674958
4[a]	3	1	1	1	5.744	5.743	-0.0001147	-0.001998485
5[a]	3	2	2	2	3.159	3.157	-0.0019475	-0.061637254
6[a]	3	3	3	3	2.329	2.329	0.000783	0.033619825
7[a]	3	1	2	3	1.967	1.967	0.0002706	0.013757597
8[a]	3	2	3	1	5.435	5.436	0.0016132	0.02968192
9[a]	3	3	1	2	3.057	3.056	-0.0005107	-0.016706351

[a] These trials are the testing trials

Table 2: Training and Testing Data of Experiments by ANN

Experiment	Feed	Depth of cut	Cutting velocity	Nose radius	Actual Surface roughness	Predicted Surface Roughness	Error	Error Percentage (%)
pruns	**F**	**DOC**	**V**	**R**	**Ra**	**Ra**		
	mm/rev	**mm**	**m/min**	**mm**	**microns**	**microns**		
1	1	1	1	1	1.46	1.458	-0.0016888	-0.1156714
2	1	2	2	2	0.972	0.975	0.003201	0.3290969
3	1	3	3	3	1.619	1.63	0.0109568	0.6766265
4	1	1	2	3	0.891	0.889	-0.0016253	-0.1823474
5	1	2	3	1	1.872	1.849	-0.0222859	-1.1904898
6	1	3	1	2	2.676	2.674	-0.0019026	-0.0710915
7	1	1	3	2	1.308	1.311	0.0033374	0.2551551
8	1	2	1	3	0.872	0.872	0.0002791	0.0319975
9	1	3	2	1	1.347	1.347	0.0003642	0.027032
10	2	1	2	3	1.331	1.329	-0.0018046	-0.1355485
11	2	2	3	1	2.224	2.215	-0.0096072	-0.4318503
12	2	3	1	2	1.915	1.913	-0.0015327	0.0800244
13	2	1	3	2	1.133	1.138	0.005216	0.46
14	2	2	1	3	1.233	1.23	-0.0027042	-0.2192068
15	2	3	2	1	1.966	1.968	0.0020765	0.1056059
16	2	1	1	1	2.05	2.05	-0.0000777	-0.003817
17	2	2	2	2	1.77	1.762	-0.0074304	-0.4197999
18	2	3	3	3	1.3	1.316	0.0163031	1.2540874
1[a]	3	1	3	2	3.201	3.223	0.0228954	0.7152584
2[a]	3	2	1	3	1.754	1.754	0.0009898	0.0564355
3[a]	3	3	2	1	4.913	4.914	0.0004769	0.0097062
4[a]	3	1	1	1	5.744	5.744	0.0005831	0.010153
5[a]	3	2	2	2	3.159	3.158	-0.0013054	-0.0413167
6[a]	3	3	3	3	2.329	2.335	0.0061787	0.265
7[a]	3	1	2	3	1.967	1.977	0.0101922	0.5181632
8[a]	3	2	3	1	5.435	5.427	-0.007563	-0.139155
9[a]	3	3	1	2	3.057	3.057	0.0003323	0.0108694

[a] These trials are the testing trials

algorithm inherits some salient features of the original back propagation neural network algorithm. As a consequence, structure identification and parameter adjustment can be carried out simultaneously. Structure identification includes the generation and deletion of neurons and hidden layers while parameter adjustment involves adjustment of weights. Cascaded Correlation Artificial Neural Network has four inputs corresponding to the surface roughness, two hidden layers and the output estimates the interference component. First, the Back Propagation (BP) neural networks learning algorithm was developed. In order to appreciate the improvements of the proposed Cascaded Correlation Artificial Neural Network learning algorithm over the original Back Propagation algorithm, it is important for the readers to understand the intermediate results achieved by the Back Propagation algorithm.

3.5. Simulation Studies and Performance Evaluation

MATLAB simulation studies are carried out in this section [19]. The BP is one of the popular paradigms in neural network based approaches. Cascaded Correlation Artificial Neural Network approaches are essentially based on it to employ offline clustering to identify the structure and the error back propagation (gradient descent) algorithm to tune free parameters. The process parameters considered are cutting speed (*V*), feed (F), depth of cut (*D*) and nose radius (R). Thus, the input layer of the neural network contains four neurons while the output layer has a single neuron corresponding to the predicted value of surface roughness. For the ease of comparison, Root Mean Square Error, which is defined as follows, is selected as the performance index:

$$RMSE = \sqrt{\frac{\sum_{k=1}^{n}(x(k) - x^{\wedge}(k))^2}{n}}$$

Where x^(k) and x(k) are the k^{th} reproduced signal by the CCANN and the desired output respectively and n is the number of incoming patterns.

4. Validation of Experimental Data

The proposed methodology is used to train the network for dry turning of SS420 materials with uncoated tungsten carbide tools. The results obtained are discussed in the following sections. For generating the training data for neural network, three levels of speed, feed, depth of cut and nose radius are taken. The best network topology is the one with four hidden neurons. A learning rate of 0.01 is used. Thus eighteen experiments act as training data for dry turning. In this case, nine randomly designed data were used for testing. Table 1 and Table 2 show the training and testing data by CCANN and ANN methods respectively.

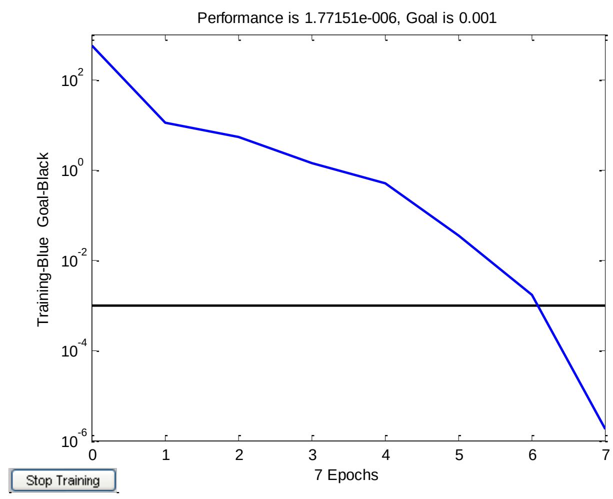

Fig. 2 Training Performance Chart for CCANN

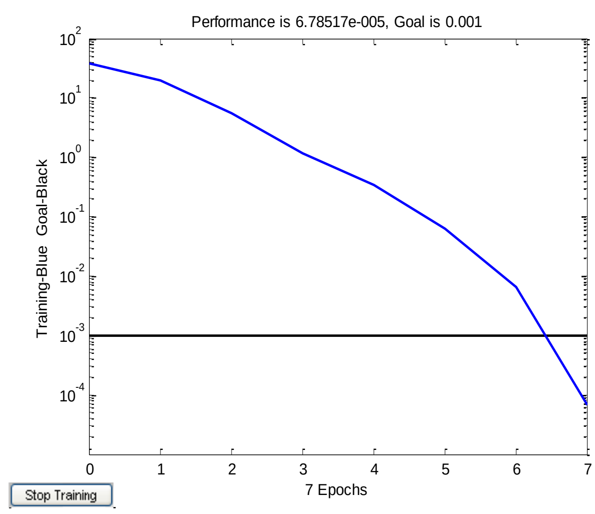

Fig.3 Training Performance Chart for ANN

Figure 2 and 3 shows the training performance chart for CCANN and ANN respectively. It is seen that the goals (0.001) and epochs (7) are the same but the performance values are 1.77151e-006 for CCANN and 6.78517e-005 for ANN methods. The deviation of the predicted most likely estimate from the experimental data is as follows. The absolute error in prediction for validation data is 0.0236 for CCANN and 0.142 for ANN.

4. Conclusion

In this paper, a new learning algorithm, termed Cascaded Correlation Artificial Neural Network learning algorithm that inherits the salient features of the original Back Propagation learning algorithm and is capable of predicting the surface roughness has been proposed. The proposed Cascade Artificial Neural Network learning algorithm has been demonstrated to be suitable for optimization of cutting parameters. In summary, the proposed algorithm has the following advantages.

i. Once the proposed Cascade Artificial Neural Network is completely trained, the response would be very fast compared to Back Propagation Artificial Neutral Network.
ii. The learning speed and parameter adaptation are fast and efficient. By employing this algorithm in the parameter optimization phase, low computation load and less memory requirements have been achieved. Simulation studies clearly demonstrate the effectiveness and superiority of the proposed Cascaded Correlation Artificial Neural Network algorithm.
iii. It is observed that in most of the cases, the experimental value is close to the most likely estimate and within the upper and lower estimates.

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