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Predictive Modeling for Power Consumption in Machining using Artificial Intelligence Techniques

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Abstract

The objective of this work is to highlight the modeling capabilities of artificial intelligence techniques for predicting the power requirements in machining process. The present scenario demands such types of models so that the acceptability of power prediction models can be raised and can be applied in sustainable process planning. This paper presents two artificial intelligence modeling techniques - artificial neural network and support vector regression - used for predicting the power consumed in machining process. In order to investigate the capability of these techniques for predicting the value of power, a real machining experiment is performed. Experiments are designed using Taguchi method so that effect of all the parameters could be studied with minimum possible number of experiments. A L_{16} (4^3) 4-level 3-factor Taguchi design is used to elaborate the plan of experiments. The power predicted by both techniques are compared and evaluated against each other and it has been found that ANN slightly performs better as compare to SVR. To check the goodness of models, some representative hypothesis tests *t*-test to test the means, *f*-test and Leven's test to test variance are conducted. Results indicate that the models proposed in the research are suitable for predicting the power.

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1. Introduction

Energy efficiency and environment impact have become important benchmarks for assessing any industry both globally and domestically due to sustainability issues and manufacturing industry is no exception. The energy efficiency of machines tools is generally very low particularly during the discrete part manufacturing and users in the automotive industry demand more often an indication for new acquisitions of how much energy a machine tool will expectedly consume during operation. The factor energy efficiency is therefore important evaluation criterion for new investment in machinery and equipment in addition to the classical parameters accuracy, performance, cost and reliability. The large number of interrelated parameters (cutting speed, feed, depth of cut, tool geometry, work piece and cutting tool properties, etc.) that influence the power consumption during machining on a machine tool makes the development of an appropriate predictive model a very difficult task. As a result analytical, numerical and artificial intelligence methods have been developed for the power consumption prediction. A lot of research has been done in last 60 years on the optimization of machining parameters for surface roughness, tool wear, forces, etc but a little research has been done to minimize the power consumption of a machine tool. Machine tools require power during machining, build-up to machining, post machining and in idling condition to drive motors and auxiliary equipments including compressed air in CNC machine tools. However, the design of a machine tool is based on the maximum power requirement during machining of material which may be very high as compared to average power requirement of the machine tool. This leads to higher inefficiency of energy in machine tools. The optimization of machining parameters for minimum power requirement is expected to lead to the application of lower rated motors, drives and auxiliary equipments and hence save consumption of power not only during machining but as well as during build-up to machining, post machining and idling condition.

The machining process is very complex and does not permit pure analytical physical modeling [1]. Predictive models that are developed using conventional approaches such

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as the statistical regression technique (regression analysis, response surface methodology) may not describe the nonlinear complex relationship between machining parameters and machining performance [2]. Recently there has been a lot of interest to develop models for investigating the influence of machining parameters (cutting speed, tool geometry, etc.) on response parameters (cost, roughness, time etc.) using artificial intelligence techniques [3-10]. Therefore, this paper aims at predicting the power consumed in machining using artificial intelligence techniques: Artificial Neural Networks (ANN) and Support Vector Regression (SVR). Machine tools have efficiency less than 30% [11] and more than 99% of the environmental impacts are due to the consumption of electrical energy used by the machine tools in discrete part manufacturing machining processes like turning and milling [12]. Reduction in power consumption will improve the environmental impact of machine tools and manufacturing processes.

In the present study, ANN and SVR models are developed to predict power during turning operation of AISI 1045 steel. In the development of predictive models, machining parameters of spindle rpm, feed and depth of cut are considered as machining parameters. Taguchi's design of experiments is carried out to conduct experiments. Total 16 experiments are conducted to measure the power. The ANN and SVR are compared against each other using the relative error, descriptive analysis and hypothesis testing. The results of developed models are in close agreement to experimental results.

This paper is organized as follows. The experimental procedure to obtain the power values is presented in section 2. Section 3 and 4 presents the prediction of power using ANN and SVR respectively. The models proposed in section 3 and 4 are compared against each other in section 5. Finally the conclusions are highlighted in section 6.

2. Experimental Planning

The turning experiments are carried out in dry cutting conditions using HMT Lathe machine, which has a maximum spindle speed of 2300 rpm. The tool holder used is a Sandvik PTGNR 2020 K16 along with Tungsten Carbide Sandvik TNMG 16 04 12 inserts. The rake angle is $+7^0$ and the clearance angle is $+6^0$. The workpiece used is AISI 1045 steel having a diameter of 47 mm and length 365 mm. An indirect method of power measurement is used to measure the power consumed during machining. A Kistler Type 9272 4-component dynamometer is used to measure the cutting force. Dynamometer is connected to a multichannel charge amplifier (Type 5070A) by a highly insulated connection cable. The amplifier amplifies the electrical charges delivered from the dynamometer into proportional voltages and then the proportional forces are processed using Dynoware, a software package designed for this purpose. Experimental set up used in this study is shown in Fig. 1.

Experiments are designed using Taguchi method so that effect of all the parameters could be studied with minimum possible number of experiments. A L_{16} (4^3) 4-level 3-factor Taguchi design is used to elaborate the plan of experiments with the factors.

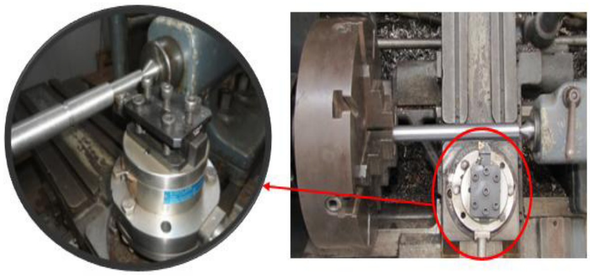

Fig. 1. Experimental setup used in this study

The choice of level is made by taking into account the capacity of the lathe and limiting cutting conditions. Three factors and their levels are given in the Table 1.

Table 1. Machining parameters and their levels

Factor	Symbol	Level 1	Level 2	Level 3	Level 4
Spindle speed (rpm)	*n*	700	910	1180	1540
Feed (mm/rev)	*f*	0.20	0.40	0.65	1.30
Depth of cut (mm)	*d*	0.6	1.0	1.4	1.8

The results obtained through a series of experiments for various sets of parametric combinations are listed in Table 2.

Table 2. Experimental design using orthogonal design and power results

Experiment No.	*n* (rpm)	*f* (mm/rev)	*d* (mm)	*P* (kW)
1	700	0.20	0.6	0.743
2	700	0.40	1.0	1.488
3	700	0.65	1.4	2.724
4	700	1.3	1.8	4.699
5	910	0.40	0.6	1.369
6	910	0.20	1.0	1.395
7	910	1.30	1.4	5.412
8	910	0.65	1.8	4.810
9	1180	0.65	0.6	2.515
10	1180	1.30	1.0	7.395
11	1180	0.20	1.4	1.589
12	1180	0.40	1.8	2.515
13	1540	1.30	0.6	4.311
14	1540	0.65	1.0	4.348
15	1540	0.40	1.4	4.004
16	1540	0.20	1.8	3.541

3. Artificial Neural Network

Experimental and analytical models can be developed by using conventional approaches such as statistical regression. Numerical models can be developed using finite element method, finite difference method, boundary element method etc [13]. On the other hand, Artificial intelligence based models are developed using nonconventional approaches such as the artificial neural network (ANN), Fuzzy logic(FL), Support Vector Regression (SVR) and Genetic Algorithm (GA).

Artificial neural networks (ANNs) are inspired by the biological nervous systems — the brain, which consists of a large number of highly connected elements called neurons [14]. The brain stores and processes the information by adjusting the linking patterns of the neurons. As in nature, the network function is determined largely by the connections between elements. We can train a neural network to perform a particular function by adjusting the values of the connections (weights) between elements. Commonly neural networks are adjusted or trained, so that a particular input leads to a specific target output. Typically many such input/target pairs are used in this supervised learning, to train a network.

In this study, the neural network toolbox of MATLAB software package is used to predict the power. An optimal neural network structure used in this study is shown in Fig. 2. It consists of three layers which are the input layer, hidden layer and output layer. The network structure has three nodes in the input layer, three nodes in the hidden layer and one node in the output layer. Three nodes for the input layer stand for the rpm, feed and depth of cut. One node for the output layer is for the power.

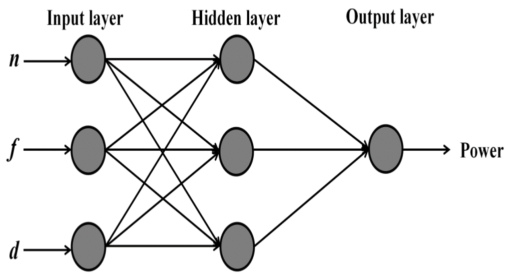

Fig. 2. ANN structure

Recommended ratio of training and testing samples could be given as percent, such as 90%:10%, 85%:15% and 80%:20% with a total of 100% for the combined ratio [15].The preferred ratio is selected as 80%:20% to fit in with the available experimental sample size of 16. The number of training and testing samples is 13 and 3. Data is normalized to a range of 0 and 1 before the training and testing process begins. A feed forward network based on back propagation algorithm is used for modeling the process. *trainlm* is used as a training function and *learngdm* as learning function to reduce the value of error based on the back propagation algorithm. *MSE* as a performance function is used to determine the error in prediction. A *tansig* transfer function in hidden layer and a *purelin* transfer function in the output layer are used to map the power values. The results obtained from the ANN modeling are shown in Table 3.

4. Support Vector Regression

A support vector machine (SVM) is a part of supervised learning for creating a function from the training data. The training data consists of pair of input objects and desired outputs. The objective is to predict the value of function for any valid input data after learning through a finite number of training examples. When SVM is applied to regression problems, then it is called support vector regression (SVR) [16]. In regression learning problem, the learning machine is given l training data from which it attempts to learn input output relationship $f(x)$. A training data set is given in pairs (x_i, y_i), $i = 1, \ldots, l$ where $x_i \in R^n$ and y_i is the actual output value. The SVR considers the following approximate function [17]:

$$f(x, w) = \sum_{i=1}^{N} w_i\, \varphi_i(x) = w^T x + b$$

where $\phi i\ (x)$ are called features, w is the weight and b is bias. Thus a linear regression hyperplane $f\,(x,\ w) = w^T\ x + b$ is estimated by minimizing a risk function

$$R = \frac{1}{2}\|w\|^2 + C\left(\sum_{i=1}^{l} |y_i - f(x_i, w)|_\varepsilon\right)$$

where C is the cost function, ε is the insensitive loss function and

$$|y - f(x, w)|_\varepsilon = \begin{cases} 0 & \text{if } |y - f(x, w)| \le \varepsilon, \\ |y - f(x, w)| - \varepsilon & \text{otherwise} \end{cases}$$

An online SVR toolbox for SVR modeling developed by [18] in MATLAB has been used for predicting the power in turning operations. The input parameters have been normalized between 0 and 1. The training set x a combined vector of all the three input parameters (n,f,d) and the training set y of response parameter power. Sixteen sets of input-output pairs from Table 2 have been used for training of the SVR model. Training parameters are used as: insensitive loss function ε = 0.01; C =1000; kernel type = radial basis function (RBF); kernel parameter = 30. SVR checks the verification of Karush–Kuhn–Tucker (KKT) conditions and simultaneously trains the data one by one by adding each sample to the function. If the KKT conditions are not verified the sample is stabilized using the stabilization technique else the sample is added. To optimize the values, the stabilization technique dynamically changes the SVR parameters, insensitive loss function and cost function. Table 3 shows the power values predicted from the SVR modeling.

5. Comparative Evaluation of Proposed Models

The relative percentage error between the values predicted by the two methods and the experimental values of the power are computed and shown in Table 3. Fig. 3 reveals that the SVR has negligible error for 15 experimental values and 23% error for remaining 1 experiment, while the error observed in

ANN is less than 5% for all the experiments except experiment nine and fifteen where the error is 9.8% and 6.6%.

The mean relative error in ANN and SVR is 1.75% and 1.86% respectively. It shows that the well trained network model can take an optimal performance and has a greater accuracy in predicting power as compare to SVR. Both the methods are suitable for predicting the power in an acceptable range. But, the model generation and training procedure of ANN took more time as compare to SVR.

Table 3. Power predicted using ANN and SVR with relative error

	Power			Relative Error	
S. No.	Experimental	ANN	SVR	ANN	SVR
1	0.743	0.748	0.753	0.684	1.326
2	1.488	1.443	1.498	3.036	0.660
3	2.724	2.738	2.734	0.512	0.369
4	4.699	4.685	4.689	0.306	0.210
5	1.369	1.369	1.379	0.005	0.733
6	1.395	1.382	1.405	0.944	0.690
7	5.412	5.189	5.402	4.129	0.190
8	4.810	4.780	4.800	0.619	0.212
9	2.515	2.269	2.525	9.797	0.403
10	7.395	7.392	5.700	0.038	22.927
11	1.589	1.585	1.599	0.216	0.646
12	2.515	2.515	2.525	0.005	0.403
13	4.311	4.311	4.301	0.001	0.222
14	4.348	4.311	4.338	0.870	0.240
15	4.004	3.741	3.994	6.565	0.243
16	3.541	3.550	3.531	0.250	0.289

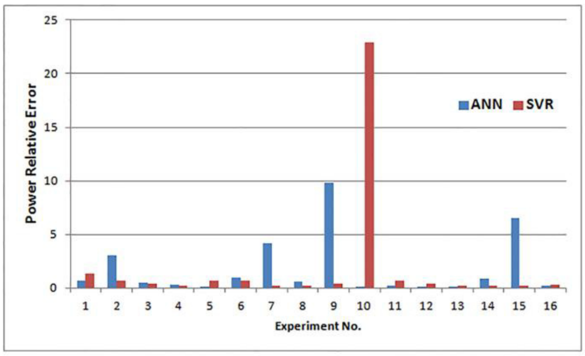

Fig. 3. Power relative error (%) for ANN and SVR

The descriptive statistics of the errors are also calculated for the two models as shown in Table 4. This table illustrates error mean, standard error mean, standard deviation, median, minimum and maximum errors. This table shows that ANN clearly outperforms SVR in all aspects.

Table 4. Descriptive statistics for error comparisons

Response	Models	Mean	SE Mean	Std dev.	Range
Power	ANN	1.749	0.705	2.821	9.796
	SVR	1.86	1.41	5.63	22.74

To compare the goodness of fit of the ANN and SVR models, some representative hypothesis tests are conducted and results are shown in Table 5. These tests are *t*-test to test the means, *f*-test and Levene's test for variance. In all these tests, the *p*-values are greater than 0.05, which means that the null hypothesis cannot be rejected. All the p-values in the Table 5 also indicate that there is no significant evidence to conclude that the experimental data and the data predicted from ANN and SVR models differ. Therefore, both prediction models have statistically satisfactory goodness of fit from the modeling point of view.

Table 5. Hypothesis testing to check the goodness of fit

95 % CI	ANN	SVR
Mean paired *t*-test	0.43	0.336
Variance *f*-test	0.975	0.615
Levene's test	0.960	0.698

From the above comparisons, it can be concluded that ANN is better than the SVR method in predicting power values during turning operations. It is evident that ANN and SVR models provide good prediction capabilities because they generally offer the ability to model more complex non-linearity and interactions. Further, ANN and SVR prediction models can be easily integrated with the optimization methods such as genetic algorithms in order to determine the optimum cutting conditions for desired response parameters.

6. Conclusions

This paper presents Artificial Neural Network and Support Vector Regression models for predicting the power consumed during the machining. Both the models have been evaluated for their validity using descriptive statistics and hypothesis testing. The predicted power results were found to be in close correlation with the actual experimental results. However, the ANN model has shown slightly the better performance as compare to SVR model. The performance of SVR model can be further enhanced by varying the values of cost function and insensitive loss function. The ANN and SVR models developed in this paper can aid the simulation, prediction, optimization, and improvement of response parameters and the selection of process parameters in machining processes. The predictive models are expected to help in fine tuning the optimum machining parameters so that the power consumption during machining can be reduced.

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