Advances in Engineering Software 78 (2014) 16–27

Contents lists available at ScienceDirect

Advances in Engineering Software

journal homepage: www.elsevier.com/locate/advengsoft

Stepwise approach for the evolution of generalized genetic programming model in prediction of surface finish of the turning process

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ARTICLE INFO

Article history:
Received 31 March 2014
Received in revised form 2 June 2014
Accepted 17 August 2014
Available online 14 September 2014

Keywords:
Surface roughness prediction
Surface property
Turning
Genetic programming
Stepwise regression
Support vector regression

ABSTRACT

Due to the complexity and uncertainty in the process, the soft computing methods such as regression analysis, neural networks (ANN), support vector regression (SVR), fuzzy logic and multi-gene genetic programming (MGGP) are preferred over physics-based models for predicting the process performance. The model participating in the evolutionary stage of the MGGP method is a linear weighted sum of several genes (model trees) regressed using the least squares method. In this combination mechanism, the occurrence of gene of lower performance in the MGGP model can degrade its performance. Therefore, this paper proposes a modified-MGGP (M-MGGP) method using a stepwise regression approach such that the genes of lower performance are eliminated and only the high performing genes are combined. In this work, the M-MGGP method is applied in modelling the surface roughness in the turning of hardened AISI H11 steel. The results show that the M-MGGP model produces better performance than those of MGGP, SVR and ANN. In addition, when compared to that of MGGP method, the models formed from the M-MGGP method are of smaller size. Further, the parametric and sensitivity analysis conducted validates the robustness of our proposed model and is proved to capture the dynamics of the turning phenomenon of AISI H11 steel by unveiling dominant input process parameters and the hidden non-linear relationships.

1. Introduction

Components produced during the turning operation have critical features that require specific surface finish [1]. Surface roughness is a widely used index for the measure of product quality. Hence, achieving desired surface roughness is of prime importance for the functional behaviour of the component. Past studies reveal that surface roughness depends on process parameters such as tool geometry, cutting conditions and work piece properties. These process parameters may be optimised for obtaining minimum cost and minimum production time. However, for obtaining the optimal input process parameter settings, the surface roughness needs to be predicted accurately. Hence, the modelling of turning process has attracted a great community of researchers with the purpose of reduction of overall cost of the engineering component [2]. With the use of numerically controlled CNC machines, the need for process modelling and optimisation is strengthened.

Considerable amount of research has been done in the prediction of surface roughness of the turning process [3–10]. Researchers have developed physics-based models to understand the behaviour of turning, but this may be a challenging task with the availability of partial information about the process [2,11]. The empirical modelling based only on the given data is a possible route for the modelling of the process. For this purpose, several empirical modelling methods such as regression analysis, artificial neural networks (ANN), support vector regression (SVR), fuzzy logic (FL) and genetic programming (GP) have been extensively applied in the prediction of surface roughness [12–16].

The regression analysis is based on statistical assumptions, and thereby induces uncertainty in the prediction ability of the models [17–19]. These models cannot be used to generalise the process data. ANN is well known for capturing the dynamics of the process. However, the optimal architecture of ANN is determined either through trial-and-error approach or by hybridising it with heuristic optimisation methods such as genetic algorithm (GA), and particle swarm optimization. This indicates that some skills/knowledge is needed to select the optimal architecture of ANN for faster training and better accuracy of the model [20–24]. SVR based on principle of SRM, is known for injecting generalisation ability in the models. Least square-support vector machines (LS-SVM) variant of SVR has been used for predicting the performance of turning process

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http://dx.doi.org/10.1016/j.advengsoft.2014.08.005

[7,25,26]. However, it does not provide explicit formulation between the input and output process parameters, and gives output values in crisp form.

FL models mostly used for modelling turning process are Mamdani and adaptive neuro-fuzzy inference system [27–30]. The formulation of FL model requires expert knowledge to formulate the fuzzy rules. Researchers have carried out additional set of experiments to test the empirical models, but it involves high labour costs and results in increase in overall cost of the product [31,32].

The applications for the explicit formulation of the performance of machining process using evolutionary approach GP have been on the rise [33–38]. The main advantage of GP over the regression analysis and other statistical modelling techniques is that it has the ability to generate mathematical equations without assuming any prior form of the existing relationships. GP and its variants have been successfully applied for modelling the performance of various non-conventional and machining processes [39,40]. The performance attributes measured were cutting force, surface roughness, tool wear, etc. Other variant of GP that uses set of genes for the formulation of model is multi-gene genetic programming (MGGP).

The peculiarity of MGGP method [41,42] is that each model participating in its evolutionary stage is the combination of several genes combined using the least squares method. The applications of MGGP method suggest that it performs better than the traditional GP method [43–45]. In traditional GP method, the model is a single tree/gene expression whereas in MGGP, the model formed is a linear combination of several trees/genes. Gandomi and Alavi [46–48] in his work demonstrated the usefulness of MGGP approach in designing the non-linear models based on the data obtained from the complex non-linear systems. Past studies reveal that MGGP method provides a fast and cost-effective explicit formulation of a mathematical model based on multiple variables with no existing analytical models. Despite remarkable capabilities of MGGP method [49–54], it is found that during the combination mechanism using least squares method in its evolutionary stage, the occurrence of genes of lower performance can degrade the performance of the MGGP model [55–58]. This limitation of the MGGP method has motivated us to develop modified MGGP (M-MGGP) method by sensibly selecting the relevant genes of higher performance for the combination mechanism.

In the present work, a M-MGGP method is proposed and applied to the modelling of surface roughness of the turning process. In this method, a stepwise regression approach is introduced for the combination of genes. Unlike least squares method, the stepwise approach selectively eliminates redundant/poor performing genes and thus only combines the high performing ones. One objective of the present work is to compare the performance of the M-MGGP model to those of the standardized MGGP approach, SVR and ANN. Sensitivity and parametric analysis is then conducted for the proposed model to accentuate the principle behind the process and examine the dominant input parameters.

Table 1
AISI H11 steel composition.

Composition	(wt%)
C	0.35
Cr	5.26
Mo	1.19
V	0.50
Si	1.01
Mn	0.32
S	0.002
P	0.016
Other components	1.042
Fe	90.31

Table 2
Input variables used in turning process.

Process input variable	Low (−1)	Centre (0)	High (+1)	Unit
Cutting speed	120	180	240	m/min
Feed rate	0.08	0.12	0.16	mm/rev
Cutting time	7	14	21	Min

Table 3
Cutting tool geometry parameters and surface roughness values.

Trial No.	Cutting speed (x_1)	Feed rate (x_2)	Cutting time (x_3)	Surface roughness (y)
1	120	0.08	7	0.263
2	120	0.08	14	0.295
3	120	0.08	21	0.315
4	120	0.12	7	0.820
5	120	0.12	14	0.838
6	120	0.12	21	0.888
7	120	0.16	7	0.572
8	120	0.16	14	0.748
9	120	0.16	21	0.874
10	180	0.08	7	0.218
11	180	0.08	14	0.274
12	180	0.08	21	0.347
13	180	0.12	7	0.395
14	180	0.12	14	0.432
15	180	0.12	21	0.494
16	180	0.16	7	0.751
17	180	0.16	14	0.813
18	180	0.16	21	0.901
19	240	0.08	7	0.249
20	240	0.08	14	0.222
21	240	0.08	21	0.280
22	240	0.12	7	0.976
23	240	0.12	14	1.200
24	240	0.12	21	1.440
25	240	0.16	7	0.830
26	240	0.16	14	1.359
27	240	0.16	21	2.240

2. Experimental details of turning process

In the present work, the turning phenomenon to be modelled is referred from an earlier study conducted on modelling and optimisation of hard turning of AISI H11 steel using response surface methodology [59]. The experiments were performed in dry conditions using lathe type SN40C with a spindle power of 6.6 KW. The sample material used was AISI H11 hot work steel which is often used for the manufacture of diecasting moulds, dies and helicopter rotor blades. The composition of AISI H11 steel is shown in Table 1. The dimensions of the material is 80 mm in diameter and is hardened to 50 HRC. The input variables considered were cutting conditions such as cutting speed, feed rate and cutting time and the output variable was surface roughness. The input variables with its low-centre-high levels used are shown in Table 2 [59].

Twenty-seven sets of data samples as shown in Table 3 are considered in this study in the turning of AISI H11 steel. These data samples were collected based on L_{27} standard full factorial 3-level experimental design. For the appropriate selection of training and testing data set, the Kennard and Stone (K–S) algorithm [60] is used to divide the data set into training and testing. This algorithm selects the training and testing data in such a way that the whole data set is distributed uniformly throughout the domain. Several applications of the K-S algorithm are reported [60–62]. Table 3 shows the set of data samples after the Kennard and Stone algorithm have been