ANN APPROACH FOR MODELLING ORTHOGONAL CUTTING

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1. Introduction

Machining is a complex process involving very large strains and strain-rates, which cause large temperature increase. Since most process variables are difficult to measure, analytical and numerical modelling of chip formation are versatile and reliable approaches to obtain local information on some variables on the workpiece and the cutting tool [1].

Recently, artificial neural networks (ANN) have been used to simulate cutting, since this technique is fairly robust and frequently converges to the desired solution. The main drawback of ANN the need of large data points for training and validation. [2] Using results obtained from validated numerical models to train the network, diminishes the experimental work significantly. Finite element analysis has played an important role in simulating and understanding the metal cutting process by having an insight look at what is going on during cutting, which is hard to achieve by experimental or analytical methods.

The aim of this paper is to simulate cutting with a radial basis function network (RBFN). This is not commonly used in cutting simulation, although it has some advantages when compared with multilayer perceptron (MLP) neural networks. The neural network is trained with results obtained from numerical model, mainly cutting forces and shear angle. This work presents briefly the numerical model used in the generation of data, the characteristics of the ANN approach and its training and validation. Results showed the ability of the neural network to predict accurately cutting parameters.

2. Numerical model

A plane strain A.L.E. model was developed in ABAQUS/Explicit. A thermo-mechanical coupled analysis was developed, with CPE4RT element type (see ABAQUS manual). These are plane strain, quadrilateral, linearly interpolated, and thermally coupled elements with automatic hourglass control and reduced integration, for A.L.E. formulation. The workpiece material was modelled using the Johnson-Cook (JC) constitutive model. The physical properties and the constants of the JC model for the work-piece material (AISI 316L) and the properties of tool material (Kennametal K313) have been found in recent work in literature [3]. The tool is fixed and the cutting speed is applied to the workpiece. Cutting takes place in plane strain conditions and continuous chip formation are assumed. Details of the A.L.E. model are shown in [4].

3. Neural network

Simulation of cutting processes is mostly achieved with multilayer perceptron (MLP) neural networks. However, MLP networks suffer from local minima problems and long computation time. The radial basis function network (RBFN) is an alternative network that has been reported to be faster and at times more accurate, as compared to a MLP neural network [5].

RBFN is a feed-forward network that is often used as a multidimensional interpolation technique. A RBFN is a local network whereas the MLP performs a global mapping. The basic architecture of the RBFN has three layers. The input layer composed of the vector of input variables. The hidden layer transforms the data from the input space by applying a non-linear function. Frequently, a Gaussian function is used. Finally, the output layer that applies a linear combination of the hidden layer outputs.

A common learning strategy for RBFN is the hybrid learning. However, this procedure has an important drawback because the radial basis centers are arbitrary selected. Here, the orthogonal least square (OLS) algorithm will be used as learning method (see, [6]). This algorithm allows selecting a suitable center from a large set of candidates. The learning and validation steps will be performed by using a cross-validation (CV) technique. This technique allows selecting the best model when the amount of data is limited. The CV is a method for estimating a generalization error based on resampling. In CV the data set is split into two parts. The first part is denoted as training set and is used to fitting the model. The second part is denoted as validation set and is used to measure how well the model fits this new data, that is, to compute the prediction error. The best model is the one with the smallest average prediction error, computed based on all (or some) different ways of data splitting. Different types of CV have been proposed in the literature. In this work, the Monte Carlo cross-validation (MCCV) proposed by [7], is used.

4. Results

The input variables of the model are the rake angle X_1 and the friction coefficient, X_2. The output variables are the cutting force, Y_1, thrust force, Y_2 and shear angle, Y_3. The values of the input variables are $X_1 = -6,0,6,8$ and $X_2 = 0,0.5,0.1,...,0.4$. A set of $n = 30$ multivariate observations are used. From this set, a sample of $n_v = 5$ is extracted to be used as validation subset. Then, the learning subset has $n_l = 25$ observations. For each candidate model, a total of $B = 10000$ subsets of n_v are randomly extracted. The OLS method is used as learning algorithm.

The results obtained shows that the best model is a RBFN with 4 hidden units. The total average mean square error using the validation subsets is $MSE = 0.0011$. The average mean square error for each predicted variable is: $MSE(Y_1) = 0.0026$, $MSE(Y_2) = 0.0006$ and $MSE(Y_3) = 0.0002$.

6. Acknowledgments

The authors acknowledge to the Ministry of Science and Technology of Spain, the financial support obtained for this work with the Project CYCIT DPI2005-08018

7. References

[1] H. Miguélez, R. Zaera, A. Rusinek, A. Moufki, A. Molinari, Numerical modelling of orthogonal cutting: influence of cutting conditions and separation criterion, *Journal de Physique IV*, **134** (2006) 417-422.

[2] D. Umbrello, G. Ambrogio, L. Filice, R. Shivpuri, An ANN approach for predicting subsurface residual stresses, and the desired cutting conditions during hard turning, *Journal of Materials Processing Technology* **189** (2007) 143–152

[3] M. Nasr, E.G. Ng, M.A. Elbestawi, Modelling the effects of tool-edge radius on residual stresses when orthogonal cutting AISI316L, *International Journal of Machine Tools & Manufacture*, **47**, (2007) 401–411.

[4] M.H. Miguélez, R. Zaera, A. Molinari, R. Cheriguene, A. Rusinek, Residual stresses in orthogonal cutting of metals: the effect of thermomechanical coupling parameters and of friction, *Journal of Materials Processing Technology*, (submitted 2008)

[5] S. Chen, C. Cowan and P (1991). Grant. Orthogonal Least Squares Learning Algorithm for radial Basis Function Networks, *IIEE Trans. Neur. Netw.*, **2**, 302-309.

[6] J. Shao (2003). Linear Model Selection by Cross-Validation, *J. Amer. Stat. Assoc.*, **88**, 486-494.

[7] S. Haykin (2007). *Neural networks: A comprehensive foundation*, 7 ed. Prentice Hall, Harlow.