HIERARCHICAL NEURAL NETWORK MODELLING OF TURNING OPERATIONS FOR SIMULATION PURPOSE

Oliver Hornyák[†], Ferenc Erdélyi[†], and Tibor Tóth[†]

[†] University of Miskolc, Institute of Information Science
Dept. of Information Engineering, 3515 Miskolc-Egyetemváros, Hungary
email: hornyak @ait.iit.uni-miskolc.hu
erdelyi@ait.iit.uni-miskolc.hu
toth@ait.iit.uni-miskolc.hu

Abstract

This paper presents an Artificial Neural Network (ANN) model to predict cutting force, torque, power and energy consumption and other important factors for turning operation. The input data required for the training of ANN has been provided through series of turning experiments. From the numerical results obtained it is possible to set up a second ANN which can provide data to characterise the quality of the workpiece.
This paper deals with the set up of ANNs including the internal architecture as well as the eligibility of input-output variables. The effectiveness of the training has been also investigated. The bounds within the trained ANN is valid has been also examined and presented in this paper.

1 Introduction

In modern manufacturing the 80 % of metal parts are machined by means of cutting. The reason of this fact is that in most cases the geometry of cutting tools are relatively simple; and the shaping process on the machine tools is based on NC path generation with the part geometric model. In general, other types of manufacturing cannot compete with cutting on required geometric accuracy and smoothness.

The importance of modelling machining operations has been recognised in machine tool communities. There are various types of models according to the scope of the investigation. In general, these models are complex, non-linear models and have a difficult internal relationship between their input and output variables.

This paper focuses on technical-economic modelling of NC turning operations. A hybrid hierarchical model will be introduced which is appropriate for supporting simulation tasks of turning operation.

The simulation of cutting operation can be carried out at six abstract levels. They are as follows:

- physical level,
- operation element level,
- feature level,
- operation level,
- job level,
- production order level.

At the first three levels the physical processes of the technology and the continuous state variables are of great importance. Therefore such models are required, which represent the geometrical, kinematical, dynamical and physical characteristics of cutting. The latter three levels belong to the scope of Event Driven Discrete Modelling (EDDM), which does not correspond to the objective of this paper.

1.1 OPERATION LEVEL MODEL OF TURNING

The five aspects of operation level model of turning which have the capability to support management decisions are as follows (Erdélyi & Hornyák, 2002):

- geometrical relations,
- kinematical relations,
- dynamical relations,
- technological relations,
- technical-economic relations.

The latter one plays a very important role in modern manufacturing as being the key issue of a competitive market. Nevertheless, it requires a very sophisticated model.

1.2 Process modelling with Neural Networks

Due to the nonlinear characteristic of the models of turning operations it is expedient to use Artificial Neural Networks. Here a hybrid approach is introduced. This uses ANNs for estimating the cutting force which is a nonlinear function of depth of cut, federate and cutting speed and also depends on material properties and environment variables. The model also uses analytical approach where possible, for example calculating the cutting power, torque, energy consumption or the Material Removal Rate (MRR).

At the fifth level the model introduces a second ANN to predict the parameters called *management indexes* which provide all the important parameters required by the Manufacturing Execution Systems. They are as follows:

- average dimensional accuracy ($\overline{\delta_a}$),
- average surface roughness ($\overline{R_a}$),
- machining time (t_m),
- rate of rejected product (p_s),
- the optimum of MRR (Q^*),
- the efficiency of stock removal, i.e. the current MRR relative to the optimum MRR (η),
- cost-equivalent time (τ),
- machining cost, tool cost, total cost (C).

Figure 1 shows the multi level hierarchical model for modelling turning operations.

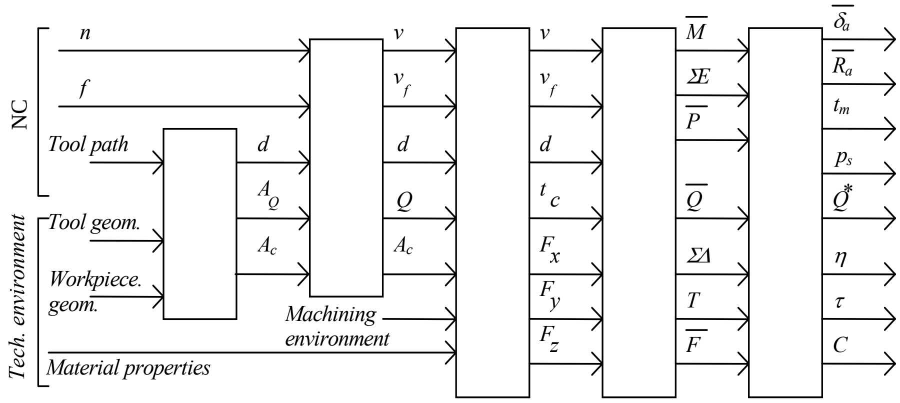

Figure 1. Multi-level model for NC machining operations

1.3 Properties of the applied model

It is noticeable that the NC programs contain most of the information which is required for modelling turning operations. This information involves the tool path geometry and technological data. Another important portion of the required data originates from the technological environment. The tool geometry and workpiece geometry is relatively easy to model. However the material properties and the effect of machining environment are difficult to be taken into account.

Some computerized methods, which are promising to solve the difficulties listed above, are as follows:

- using database of cutting parameters,
- AI methods to handle non-linearities,
- state equations to describe the dynamic behaviour of processes,
- object oriented programming methods,
- component based software engineering, as well as
- graphical representation and interactive human-machine interface.

The advantage of the model is that it is capable to handling the non-linear relationships between the state variable. It requires, however, training samples to train the Neural Network. Thus it has its advantage in medium and large batch production. The model eliminates the stochastic behaviour originated from the material properties and environment properties as these properties are regarded as constant parameter of the NN teaching activity. Notwithstanding, if these parameters have changed a new set of training data have to be collected and the training process have to be redone.

The main disadvantage of the hierarchical model structure is that any error introduced in the lower level will appear at the higher level as well. Therefore the results should be experimentally validated.

2 Training of the Neural Network

The ANN at the first level has been trained using the data collected and publishedby Prof. Tóth (Tóth 1968). The available data has been randomly split into two sets: a training set containing the 2/3 of the data and a test set to check the correctness of the training. The ANN had one hidden layer with 30 neurons while the input layer received four inputs as:

- depth of cut (d),
- feedrate (f),
- cutting speed (v) and
- cutting edge angle (κ).

On the output layer the only one neuron represented the cutting force (Fc). Several training methods have been tested and the scaled conjugate gradient method developed by Moller (Moller, 1993) provided acceptable training (convergence) speed. Figure 2 shows the layout of the two ANNs.

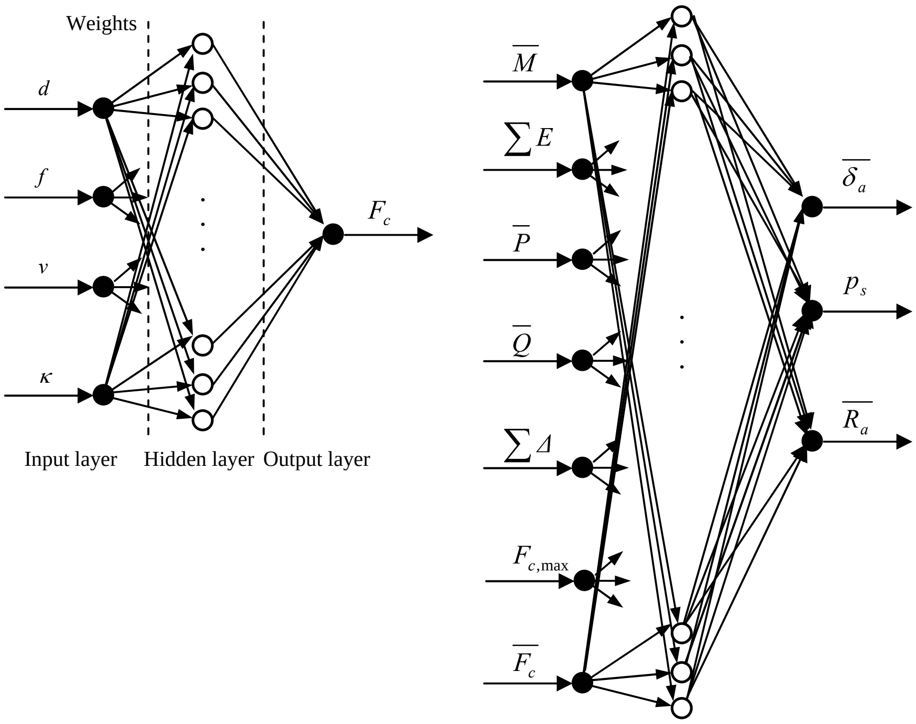

Figure 2. The proposed layout of the ANNs

The second ANN had the same internal structure and teaching as the first one, though it had more input and output neurons as it is shown on Figure 2. In the lack of experimental data some training data was generated and used.

In a real manufacturing workshop the data required for teaching the second ANN is usually available. It is generally admitted that there is a relationship between the input parameters i.e. torque, energy consumption of cutting, power used, Material Removal Rate (sometimes regarded as the technological intensity of cutting), tool wear, and the average and maximum of cutting force, and the output parameters which describes the quality of the product.

Again, some other factors are regarded as being constant thus a NN model could predict the required information with an acceptable precision.

As discussed before trained network should be validated against a test sample set. As it is shown in Figure 3 the first ANN provided quite reliable estimation on cutting force.

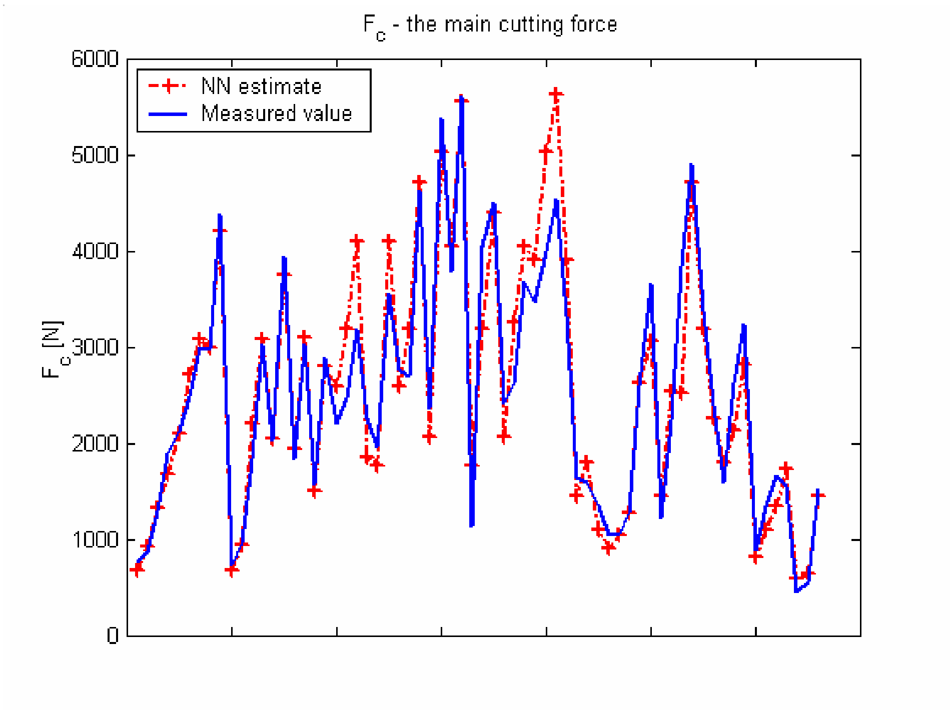

Figure 3. Checking against the test set of the sample data

Acknowledgements

This work was partially supported by the Hungarian Academy of Sciences (HAS) within the framework of Production Information Engineering Research Team (PIERT) established at the Department of Information Engineering of the University of Miskolc (Grant No. MTA-TKI 06108). The research is also connected with the bilateral project EDNA (Development of an Educational Test Bed for the Implementation of Distributed Internet Applications in Manufacturing Execution Systems) within the framework of Turkish-Hungarian Intergovernmental S&T Cooperation (Grant No. TR-4/2000). The authors gratefully acknowledge the financial support obtained from the two aforementioned sources.

The results are also connected with the project entitled “Digital Factories, Production Networks” within the framework of the National Research and Development Program founded by the Ministry of Education of Hungary (Grant No. 2/040/2002, project leader: László Monostori DSc). The authors would like to express their thanks for the partial financial support.

References

Hornyák, O. (2002), *Extended simulation of turning operations by means of intelligent methods* (*Esztergálási műveletek kiterjesztett számítógépes szimulációja intelligens módszerek alkalmazásával).* PhD thesis. p. 115

Erdélyi, F. & Hornyák, O. (2002), *Extended Simulation Approach for NC Turning Operations.* The Tenth International Conference on Machine Design and Production, Cappadocia, Turkey, pp. 153-164.

Tóth, T. (1968), Process planning of turning operations based on the precision of machining, (*Esztergálás technológiai adatainak tervezése elektronikus számítógéppel a megmunkálási pontosság alapján), Doctoral thesis,* Miskolc, p. 118.

Moller, M. F. (1993), *A scaled conjugate gradient algorithm for fast supervised learning*, Neural Networks, vol. **6**, pp. 525-533.

Appendix A

Sample data v = 110 m/min r_{ε}=1.5 κ=45 ^{o}						
Number	f [mm/rev]	d [mm]	P [kW]	F_c [N]	F_m [N]	F_e [N]
1	0.1	1	3.8	415.55	257.51	180.11
2	0.158	1	4.2	568.49	525.23	218.86
3	0.2	1	4.3	723.68	662.67	217.19
4	0.316	1	4.7	949.71	704.55	255.65
5	0.4	1	5.1	1187.30	836.30	298.03
1	0.2	1.5	4.7	750.96	356.69	402.11
2	0.316	1.5	5.4	1336.12	361.60	456.85
3	0.4	1.5	6	1606.19	719.07	501.09
4	0.542	1.5	6.9	1832.51	1025.15	577.32
1	0.2	2	5.2	1253.72	937.84	380.63
2	0.316	2	6.1	1677.51	1074.20	543.47
3	0.4	2	6.8	2207.25	1421.47	752.43
4	0.542	2	7.8	2752.69	1706.94	820.12
5	0.66	2	8.5	3021.48	2105.23	762.24
1	0.2	2.5	5.6	1482.29	485.60	584.68
2	0.316	2.5	6.6	2017.92	1039.86	823.06
3	0.4	2.5	7.7	2651.64	1534.28	889.77
4	0.542	2.5	8.4	3248.09	1858.01	971.19
5	0.66	2.5	9.2	3712.10	2098.36	1074.20
1	0.2	3	6	1780.52	1425.39	689.64
2	0.316	3	7.2	2480.95	1466.60	793.63
3	0.4	3	8.1	3017.56	1492.10	948.63
4	0.542	3	9.4	3938.72	1603.94	1274.32
1	0.1	3.5	5	1094.80	753.41	486.58
2	0.2	3.5	6.5	1825.64	850.53	687.68
3	0.316	3.5	7.8	2947.91	1011.41	888.79
4	0.4	3.5	8.4	3438.41	1430.30	1132.07
5	0.542	3.5	9.8	4532.22	1666.72	1372.42
1	0.1	4	5.4	1486.22	508.16	529.74
2	0.2	4	6.9	1824.66	784.80	717.11
3	0.316	4	7.8	3032.27	2254.34	1170.33